الجمهورية الجزائرية الديمقراطية الشعبية
République Algérienne Démocratique et Populaire
وزارة التعليم العالي والبحث العلمي
Ministère de l’enseignement supérieur et de la recherche scientifique

Université Mohamed Khider – Biskra
Faculté des Sciences et de la technologie
Département de Génie Electrique
Ref/ /G.E/2016.

جامعة محمد خيضر بسكرة
كلية العلوم والتكنولوجيا
قسم: الهندسة الكهربائية
المرجع: Ref/ /G.E/2016.

Thèse présentée en vue de l’obtention
Du diplôme de

Doctorat en sciences

Spécialité : Réseaux Électriques

Gestion et contrôle optimale de l'énergie électrique sur les sites de production

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Soutenue publiquement le 26 / 04 / 2016

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الجمهورية الجزائرية الديمقراطية الشعبية
People's Democratic Republic of Algeria
وزارة التعليم العالي والبحث العلمي
Ministry Of Higher Education & Scientific Research

University Mohamed Khider – Biskra
Faculty of Science and Technology
Department of Electrical Engineering
Ref/ /G.E/2016.

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كلية العلوم والتكنولوجيا
قسم: الهندسة الكهربائية
Ref/ /G.E/2016.:المرجع

A thesis submitted for the fulfillment of
the degree of

Doctorate of Science

Option: Power System (Electrical Networks)

Optimal Management and Control of Electrical Energy on Production Sites

Presented by :

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The public thesis defense on 26 / 04 / 2016

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بسم الله الرحمن الرحيم

قال الله تعالى: ﴿إِنَّ فِي خَلْقِ السَّمَاوَاتِ وَالْأَرْضِ وَاخْتِلَافِ اللَّيْلِ وَالنَّهَارِ لَآيَاتٍ لِأُولِي الْأَلْبَابِ (190) الَّذِينَ يَذْكُرُونَ اللَّهَ قِيَامًا وَقُعُودًا وَعَلَى جُنُوبِهِمْ وَيَتَفَكَّرُونَ فِي خَلْقِ السَّمَاوَاتِ وَالْأَرْضِ رَبَّنَا مَا خَلَقْتَ هَذَا بَاطِلًا سُبْحَانَكَ فَقِنَا عَذَابَ النَّارِ﴾.

[آل عمران : 190، 191]

[In the creation of the heavens and the earth and in the alternation of the night and the day there are indeed Signs for men of understanding (190) who remember God standing, and sitting, and lying on their sides; and meditate on the creation of heaven and earth, …**]** [Aal 'Imraan:190-191]

- إهـــداء -

الحمد لله رب العالمين والصلاة والسلام على خاتم الأنبياء والمرسلين
الحمد لله الذي أنار لنا درب العلم والمعرفة وأعاننا ووفقنا إلى انجاز هذا العمل الذي أهديه إلى:

من ربتني وأنارت دربي وأعانتني بالصلوات والدعوات، إلى أغلى إنسان في هذا الوجود أمي الحبيبة،
من عمل بكد في سبيلي وعلمني معنى الكفاح وأوصلني إلى ما أنا عليه أبي الكريم أدامه الله لي،
رفيقة دربي وعوني في الحياة زوجتي العزيزة وملاكي الصغير ابنتي الحبيبة،
من حبهم يجري في عروقي ويلهج بذكراهم فؤادي، سندي في الدنيا ورفقاء دربي، إخوتي وأخواتي،
جدتي وكل أخوالي وخالاتي وأعمامي وعماتي وعائلاتهم،
كل أساتذتي المحترمين الذين تعاقبوا على تدريسي طيلة مشواري الدراسي ولم يبخلوا علي بالبذل والعطاء والبيان،
إلي أصدقائي الأعزاء وكافة الزملاء،
إلى كل باحث عن فكرة مضيئة تنير له زقاق الطريق، وإلى أصحاب العقول النيرة، والبصائر المستنيرة وكل من زرع روح المبادرة،
واسأل الله أن ينتفع به كل الدارسين، إن شاء الله.

Acknowledgments

First of all, I would like to thank God Allah for giving me strength, courage, patience and serenity during all these years of study.

I wish to express my sincere gratitude to my supervisor Prof. Djilani Ben Attous, who have been a constant source of guidance, support and encouragement throughout my Project. his extensive knowledge, rigorous research attitude, diligent working and creative thinking have inspired me and will definitely benefit my career.

My deepest gratitude is also due to the members of the jury: Prof. Srairi Kamel, Prof. Moussi Ammar, Prof. Ben Chouia Med Toufik, Prof. Betka Achour and Dr. Zellouma Laid, for serving as my committee members and taking the time to revise my thesis. I am thankful that in the midst of all their activity, they accepted to be members of the reading committee.

I also want to express my special appreciation to my parents (Malika & Mohammed Ali) for their love and continued support. I also want to thank all my family: my wife and my daughter (Zineb & Ritel), my sisters (Amena, Imene and Asmaa) and my brothers (Ahmed, Walid and Ezzeddine), and all my family and friends for their support and encouragement.

Finally to anybody who attempts to develop the ideas presented here, I hope they can be of use.

Yacine Labbi

Optimal management and control of electrical energy on production sites

Abstract

In recent years, power demand has been increasing with the industrialization development. Various management and planning tools have been used, but additional research and development are needed to bring them to the optimal utilization and control. Unit commitment (UC) and economic dispatch (ED) problems are the fundamental problem that system operators solve in order to minimize the costs associated with reliably operating electricity grids. In order to minimize the fuel cost and keep the power outputs of generators and bus voltages in their secure limits, several methods metaheuristic have been used in this work namely Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Pattern Search (PS), Big Bang–Big Crunch algorithm (BB-BC) and Artificial Bee Colony algorithm (ABC) with their hybrids. In addition, these methods have been applied to determine the commitment order of the thermal units in power generation in systems. Two new approaches have been developed and introduced in the context of our thesis called: root tree optimization algorithm (RTO) and GAGE. The results obtained by the application of the first developed method (RTO) for solving various types of ED problem, comparatively to recent methods that treat the same problem, showed a better solution quality and reducing CPU time to reach the best solution. The second GAGE based on genetic engineering operator in genetic algorithm, was developed for solving the UC problem. Thus, this method show remarkable improvements in total costs for a 10-unit test system and Algerian electrical network for a 24-hour period.

Keywords: Optimal Power Flow, Power Systems, Economic Dispatch, Unit Commitment, Pollution Control, emission, Metaheuristic, Hybrid algorithms, PSO, GA, PS, BB-BC, ABC, RTO, GAGE.

Gestion et contrôle optimale de l'énergie électrique sur les sites de production

Résumé

Au cours des dernières années, la demande de l'énergie électrique a augmenté avec le développement de l'industrialisation. Divers outils de gestion et de planification ont été utilisées, mais la recherche et le développement supplémentaires sont nécessaires pour les amener à l'utilisation et le contrôle optimale. L'engagement des unités (UC) et le dispatching économique (ED) sont les deux fondamentaux problèmes que les opérateurs du système résoudre afin de minimiser les coûts d'exploitation des réseaux électriques de manière optimale. Afin de minimiser le coût du carburant et de garder les sorties de puissance de générateurs et des tensions de bus dans leurs limites sûres, plusieurs méthodes métaheuristiques ont été utilisés dans ce travail, notamment des optimisation par essaims particulaires (OEP), Algorithme Génétique (AG), Pattern Search (PS) algorithme Big Bang-Big Crunch (BB-BC) et l'algorithme Artificiel Bee Colony (ABC) avec leurs hybrides. En outre, ces méthodes ont été appliquées pour déterminer l'ordre d'engagement des unités thermiques de production d'électricité dans les systèmes. Deux nouvelles approches ont été développées et introduites dans le cadre de notre thèse à savoir : algorithme d'optimisation de l'arbre racine (RTO) et GAGE. Les résultats obtenus par l'application de la première méthode développée (RTO) pour résoudre divers problèmes du types ED, comparativement aux méthodes récentes qui traitent le même problème, ont montré une meilleure qualité de la solution et réduire d'une manière significative le temps CPU d'exécution. La seconde, GAGE est basé sur l'opérateur de l'exploitation de l'ingénierie génétique dans l'algorithme génétique, a été développée pour résoudre le problème UC. Ainsi, cette méthode montre des améliorations remarquables dans les coûts totaux pour un système de test de 10 unités et le réseau électrique algérien pour une période de 24 heures.

Mots clés: Optimisation de l'écoulement de puissance, Réseau, Dispatching Economique, Engagement d'Unité de production, contrôle de pollution, émissions, Métaheuristiques, Algorithmes Hybrids, Optimisation par Essaims de Particules (PSO), Algorithmes Génétiques (AG), Recherche de motifs (PS), algorithme de Big Bang et de Big Crunch, Colonie d'Abeilles Artificielle (ABC), algorithme d'Optimisation des Racines des Arbres (RTO), Algorithmes Génétiques avec mécanisme de Génie Génétique (GAGE).

التحكم والإدارة المثلى للطاقة الكهربائية في مواقع الإنتاج الطاقة

الملخص

في السنوات الأخيرة، الطلب على الطاقة يزداد مع تطور التصنيع. العديد من أدوات الإدارة والتخطيط قد استخدمت، ولكن تبقي هناك حاجة الإضافة للبحث والتطوير للوصول الي الاستخدام والسيطرة المثلى. مشاكل جدولة وحدات التوليد (UC) والتوزيع الاقتصادي (ED) هي المشاكل الأساسية التي يجب على مشغلي النظام إيجاد حلول لها من أجل تقليل التكاليف استغلال الشبكات الكهربائية بشكل مثالي. حيث تهدف جدولة وحدات التوليد الي تحديد الوحدات التي يجب أن تعمل خلال فترة زمنية معينة بأقل تكلفة ممكنة لتلبية القدرة الكهربائية اللازمة للأحمال مع توافر الاحتياطي السريع المطلوب وتحقيق قيود التشغيل للوحدات. يتم صياغة المشكلة رياضيا بتقليل دالة الهدف المكونة من تكلفة الوقود وتكلفة البدء للوحدات التي يتم إدخالها للتشغيل، حيث تخضع هذه الوحدات عند تشغيلها الي مجموعة من القيود، منها حدود التوليد للوحدات، الاحتياطي السريع المطلوب لمواجهة أي حالة طلب طاقة طارئ، الحد الأدنى الفوقي لزمن تشغيل الوحدات ووقت الراحة الأدنى عند فصل الوحدات، وكذلك معدل تغير القدرة المنتجة لهدة الوحدات.

من أجل تقليل التكلفة والحفاظ على مخرجات قوة المولدات الكهربائية والفولتية الموصلات العمومية في حدودها الآمنة، عدة طرق ميتاهيروستيكية استخدمت في هذا العمل وهي استمثال عناصر السرب (PSO)، الخوارزميات الجينية (GA)، نمط البحث (PS)، خوارزمية الانفجار الكبير-الانسحاق الشديد (BB-BC)، خوارزمية مستعمرة النحل الاصطناعي (ABC)، وطرق أخرى الهجينة بينهم. وبالإضافة إلى ذلك، تم تطبيق هذه الأساليب لتحديد الجدولة المثالية لوحدات التوليد في نظم توليد الطاقة. في هذه الأطروحة قمنا بتقديم وتطوير طريقتين جديدتين تسمى: خوارزمية جذور الشجر المثالية (RTO) والخوارزمي الجيني مضاف له ميكانزيم الهندسة الجينية (GAGE). النتائج التي تم الحصول عليها من تطبيق الطريقة الأولي (RTO) لأجل حل أنواع مختلفة من مشكلة ED، مقارنة مع أساليب حديثة مطبقة على نفس التجارب، وجدنا أنها أظهرت نوعية الحل أفضل والوقت تنفيذ قليل جدا للوصول إلى أفضل الحلول. وأما الطريقة المقترحة الثانية GAGE والتي استنبطت بإضافة ميكانزيم جديد للخوارزميات الجينية وهو الهندسة الجينية، فقد طورت لأجل إيجاد حلول لمشكلة UC. وهكذا وجدنا بأن هذه الطريقة تظهر تحسناً ملحوظا في التكاليف الإجمالية لنظام الاختبار 10 وحدات ونظام الشبكة الكهربائية الجزائرية في فترة 24 ساعة مقارنة مع الطرق التقليدية لـGA والطرق المقترحة حديثا في المراجع.

كلمات مفتاحية: التدفق الأمثل للطاقة الكهربائية، أنظمة الطاقة، والتوزيع الاقتصادي، جدولة وحدات التوليد، وانبعاث أكاسيد النيتروجين، ميتاهيروستيك، خوارزميات الهجينة، استمثال عناصر السرب، الخوارزميات الجينية، نمط البحث، خوارزمية الانفجار الكبير-الانسحاق الشديد، خوارزمية مستعمرة النحل الاصطناعي، RTO، GAGE.

LIST OF PUBLICATIONS Related to the Thesis

Journal Publications

1. Y Labbi, D.B. Attous, H.A. Gabbar, B. Mahdad, A. Zidan, *A new rooted tree optimization algorithm for economic dispatch with valve-point effect*, International Journal of Electrical Power & Energy Systems 79:298-311, 2016.
2. Yacine Labbi, Djilani Ben Attous, *A Hybrid Big Bang–Big Crunch optimization algorithm for solving the different economic load dispatch problems*, International Journal of System Assurance Engineering and Management, 2016.
3. Yacine Labbi, Djilani Ben Attous, Belkacem Mahdad, *Artificial bee colony optimization for economic dispatch with valve point effect*, Frontiers of Energy, 8(4):449-458, 2014.
4. Yacine Labbi, Djilani Ben Attous, A *genetic algorithm to solve the thermal unit commitment problem*, International Journal of Power and Energy Conversion, 5(4):344-360, 2014.
5. Yacine Labbi, Djilani Ben Attous, *Environmental/economic power dispatch using a Hybrid Big Bang–Big Crunch optimization algorithm*, International Journal of System Assurance Engineering and Management, 5(4):602-610, 2014.
6. Yacine Labbi, Djilani Ben Attous, *A hybrid particle swarm optimization and pattern search method to solve the economic load dispatch problem*, International Journal of System Assurance Engineering and Management, 5(3):435-443, 2014.
7. Djilani Ben Attous, Yacine Labbi, *Application of a particle swarm optimization in an optimal power flow*, Journal of Fundamental and Applied Sciences, 2 (2):54-66, 2012.
8. Djilani Ben Attous, Yacine Labbi, *Particle swarm optimization for optimal power flow problem with non-smooth fuel cost functions*, Association for Advancement of Modeling and Simulation Techniques in Enterprises (AMSE), 83(3), 2011.
9. Yacine Labbi, Djilani Ben Attous, *Big Bang-Big Crunch Optimization Algorithm for Economic Dispatch with Valve-Point Effect*, Journal of Theoretical & Applied Information Technology, 16: 48-56, 2010.
10. Yacine Labbi, *A Hybrid GA-PS Method to solve the Economic Load Dispatch Problem*, Journal of Theoretical & Applied Information Technology, 16:48-56, 2010.

Conference Proceedings

1. Yacine Labbi, Djilani ben Attous, *Combined Economic and Emission Dispatch Using Big Bang–Big Crunch Optimization Algorithm*, ICEN'2010 – International Conference on Electrical Networks, 2010, Sidi Bel-Abbès, Algeria
2. D. Ben Attous, Y. *Labbi, Particle swarm optimization based optimal power flow for units with non-smooth fuel cost functions*, International Conference on Electrical and Electronics Engineering, 2009, ELECO 2009, Bursa, Turkey.
3. D. Ben Attous, Y. Labbi, *Particle Swarm Optimization to Solve Economic Dispatch with Valve Point Effects*, The 3rd International Conference on Electrical Engineering Design and Technologies (ICEEDT'09), 2009 in Sousse, Tunisia.

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List of Abbreviations

EDPs	Economic Dispatch Problems
ELD	Economic Load Dispatch
CEED	Combined Economic Emission Dispatch
DED	Dynamic Economic dispatch
POZ	Prohibited Operating Zones
UC	Unit Commitment
OPF	Optimal Power Flow
GA	Genetic Algorithm
PSO	Particle Swarm Optimization
PS	Pattern Search
BB-BC	Big Bang–Big Crunch algorithm
ABC	Artificial Bee Colony algorithm
GA–PS	A hybrid Genetic Algorithm and Pattern Search method,
PSO–PS	A hybrid Particle Swarm Optimization and Pattern Search method,
HBB–BC	A Hybrid Big Bang–Big Crunch method.
LP	Linear Programming
IP	Integer Programming
PSO-OPF	Particle Swarm Optimization based on Optimal Power Flow
RCGA	Ring Crossover operation for Genetic Algorithm
RTO	Root Tree Optimization algorithm
GAGE	Genetic Algorithms with Genetic Engineering operation
CI	Artificial Intelligence
SI	Swarm Intelligence
G	Generator
SO_x	Sulphur Oxides
NO_x	Nitrogen Oxides

List of Symbols

F_t	Total fuel cost of generation (\$/h or Rsh)
P_i	Real power generation of i^{th} generator (MW)
$F_i(P_i)$	Fuel cost function of i^{th} generator (\$/h or Rsh)
a_i	Cost coefficient of generator (\$/MWh^2)
b_i	Cost coefficient of generator (\$/MWh)
c_i	Cost coefficient of generator (\$)
α_i	Emission coefficient of generator (kg/MWh^2)
β_i	Emission coefficient of generator (kg/MWh)
γ_i	Emission coefficient of generator (kg)
δ_i	Emission coefficient of generator
P_D	Total load of the system (MW)
P_L	Transmission loss of the system (MW)
P_{im}, P_{in}	Real power injections at m^{th} and n^{th} buses (MW)
B_{mn}	Generalized loss coefficients (MW^{-1})
β_{i0}	i^{th} element of the loss coefficient
B_{00}	Constant loss coefficient
P_i^{max}	Maximum power produced by generator i (MW)
P_i^{min}	Minimum power produced by generator i (MW)
n	Number of generators connected in the network
T	Number of intervals in the study period
S_i^t	Reserve contribution of unit during time interval t
UR_i	Ramp-up rate limits of i^{th} unit (MW/h)
DR_i	Ramp-down rate limits of i^{th} unit (MW/h)
S_i^{max}	Maximum contribution of unit i to the reserve capacity
S_i^t	Spinning reserve of unit i
SR^t	System spinning reserve requirement for time interval t
$P_{T_{jk,min}}$ and $P_{T_{jk,max}}$	Specify the tie-line transmission capability
n_i	Number of the prohibited zones in unit i
θ	Set of units that have prohibited zones
$P_{i,j}^l$, $P_{i,j}^u$	Lower and upper bounds of the j^{th} prohibited zone
e_i and h_i	Coefficients of generator i reflecting valve point effects
a_{ip}, b_{ip}, c_{ip}	Cost coefficients of generator for the p^{th} power level
λ^0	Lambda initial
x^0	Starting point
α	Scalar to allow us to guarantee that the process of convergence
ϕ	Surface

$\nabla\Psi x$	Gradient vector
g'(x)	Familiar Jacobian matrix
Pg_i, Qg_i	Active and reactive power generations
P_i, Q_i	Active and reactive power injections at bus i
Pd_i, Qd_i	Active and reactive power demands at bus i
N	Total number of buses
Nb	Total number of load buses in the system
P_{ij}	Active power flow between buses i and j
$P_{ij,min}$, $P_{ij,max}$	Minimum and maximum limits
Nl	Total number of transmission lines
Y	Admittance matrix
S_i	Apparent power
V_i	Complex voltage at bus i
I_i	Complex current at bus i
*	Complex conjugate
π	Model of transmission lines
Y_{ij}	(i, j) element in the network admittance matrix
G	Conductance
B	Suseptance
STC	Start-up cost
C_c	Cold start cost (MBtu)
C_f	Fixed cost that includes crew expenses and maintenance expenses
C_t	Cost in Mbtu/hour for maintaining the unit at operating temperature
α	Thermal time constant of the unit
t	Time in hours the unit was allowed to cool
S_{ij}	Start-up cost of unit i at time j
D_{ij}	Shut-down cost of unit i at time j
U_{ij}	ON('1')/OFF('0') status of unit i at time j,
N	Number of units
T	Scheduling period in hours
P_{Dj}	System load demand at time j
P_{Rj}	System spinning reserve required at time j
Tcoldi	Cold-Start hours
CSC_i	Cold-Start cost
HSC_i	Hot-Start cost
$T_{ij}^{ON/OFF}$	ON/OFF period of unit i at time j
MUT_i/MDT_i	Minimum up/down time of unit i
N	Population size
p_{best}	best solution

g_{-best}	Global best
p_{-best}	Local best
C_1, C_2	Acceleration constants
w	Inertia weight
$V_i^{(k)}$	Velocity of i^{th} particle at iteration 'k'
w_{max}	Maximum value of weighting factor
w_{min}	Minimum value of weighting factor
$Iter_{max}$	Maximum number of iterations
Iter	Current number of iteration
M	Mesh trial point
Δ_k	Mesh size parameter
f_i	Fitness function
x^c	Center of mass
l	Upper limit of the parameter
r	Normal random number
x^{new}	New point x^{new}
α_1, α_2 and α_3	Adjustable parameters
P_m	Mutation rate
P_c	Crossover rate P_c
X_0	Initial points
D_w	Degree wetter
R_n	Rate of the nearest root to water
It	Iteration step
$x^{new}(It+1)$	New candidate for the iteration (It+1),
$x^{best}(It)$	Best solution to the previous generation,
i	Number of candidate,
N	Population scale,
l	Upper limit of the parameter and
randn	Normal random number between [-1, 1]
R_c	Rate of the continuous root in its orientation R_c
X(It)	Previous candidate for the iteration It
rand	Random number between [0, 1]
R_r	Rate of the random root R_r
X_r	Individual randomly selected from the previous generation
c_1, c_2 and c_3	Adjustable parameters

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General Introduction

Optimization, the best way of doing things, is obviously of great interest in the practical world of engineering. In recent years, for power system management, many important decisions are made by describing the system under study as precisely and quantitatively as possible, selecting some measures of system effectiveness, and then seeking the state of the system which gives the most desirable solution to the criteria [1]. Modem electric power systems built with nonlinear characteristics are highly interconnected with wide geographical distribution. This demands the optimization of a complex objective function under few practical constraints. Hence power system network optimization involves maximization or minimization of objective function under certain constraints [1].

operational planning of the power system involves the best utilization of the available energy resources subjected to various constraints to transfer electrical energy from generating stations to the consumers with maximum safety of personal/equipment without interruption of supply at minimum cost [1-4]. In modern complex and highly interconnected power systems, the operational planning involves steps such as load forecasting, economic dispatch, unit commitment, maintenance of system frequency and declared voltage levels as well as interchanges among the interconnected systems in power pools etc [3-4].

There are three stages in system control, namely generator scheduling or unit commitment, security analysis and economic dispatch [2].

- Economic dispatch orders the minute-to-minute loading of the connected generating plant so that the cost of generation is a minimum with due respect to the satisfaction of the security and other engineering constraints
- Generator scheduling involves the hour-by-hour ordering of generator units on/off in the system to match the anticipated load and to allow a safety margin.
- With a given power system topology and number of generators on the bars, security analysis assesses the system response to a set of contingencies and

provides a set of constraints that should not be violated if the system is to remain in secure state.

Mathematically well-defined objective and constraint functions and their derivatives must therefore be developed in order to land at a global optimum in a search procedure [4]. In order to alleviate the problems associated with traditional strategies, intelligence techniques are also explored.

This thesis deals with the application of artificial intelligence methods to the inherent issues, which govern the satisfactory delivery of electric power. It includes economic load dispatch, combined economic emission load dispatch, economic load dispatch with prohibited operating zones and unit commitment problem. The proposed work includes the state-of-the-art methods and procedures necessary for designing and developing an intelligence system. This work takes into account the theoretical investigations and practical considerations especially for mutual dependencies between intelligence techniques such as genetic algorithm, swarm intelligence, pattern search method, big bang–big crunch optimization and artificial bee colony optimization.

✓ **Objectives of the thesis**

The main objectives of the dissertation are :

(a) To provide a mathematical formulation of the various types of economic load dispatch problems in power systems such as economic load dispatch (ELD) problem,

(b) To provide an overview of the concept of Unit Commitment (UC) problem with a bibliographical survey of relevant background, the present state and potential methodologies used for solving the concern problem,

(c) To presents a comprehensive review of the methodologies, which covers a wide span of Evolutionary Computation and Meta-heuristic and hybrid approaches such as GA, PSO, PS, BB-BC, ABC and their hybrid approaches. In terms of contribution, it formulates the problem clearly and describes appropriate approaches to solve the problems,

(d) To present our proposed metaheuristic techniques and their applications on different economic dispatch problem,

(e) To implement a different types of genetic algorithms for solving unit commitment problem in a power system, implemented algorithms successfully solves both small and large scale problems and shows how much more efficient variable structure genetic algorithm,

(f) To propose a new method for optimization that is called "root tree optimization" algorithm (RTO), the robustness and efficiency of the proposed new method is validated, the proposed approach RTO has been applied to various test systems ED problem solution considering valve-point effect,

(g) To propose a novel operator for Genetic Algorithms a "genetic modification" for solving the UCP, generating unit's shows that we can find the optimal solution effectively and these results are compared with the conventional methods and various optimization approaches in the recent literature.

✓ **Organization of The Thesis**

After a general introduction to the undertaken work and the presented literature review, the main body of the thesis is structured as follows:

- A general introduction to the problem of power system optimization is presented in chapter 1. The need for intelligence based approaches is discussed, and a review of the traditional optimization strategies is traced. It includes a survey of the literature and the main objectives of the dissertation.
- Chapter 2 presents the mathematical formulation of the various types of economic load dispatch problems in power systems such as economic load dispatch (ELD), combined economic emission dispatch (CEED) and the economic load dispatch (ELD) with prohibited operating zones considering ramp rate limits.
- Chapter 3 presents formulation the UC problem considering various operating constraints, such as power balance, spinning reserve, operating limit, and minimum up/down time.
- Chapter 4 provides a general description of these metaheuristics techniques in power systems, and we briefly revise the main features of the metaheuristic approaches, focusing particularly on those used in this thesis such as Genetic Algorithm (GA), Particle Swarm Optimization algorithm (PSO), Pattern Search

method (PS), Big Bang–Big Crunch optimization algorithm (BB–BC), Artificial Bee Colony optimization algorithm (ABC), a hybrid GA–PS method, a hybrid PSO–PS method and Hybrid BB–BC optimization algorithm.

- Chapter 5 applies the proposed methods to various types of ED problem with smooth and non-smooth cost functions and it is also compared with other methods for validating their ability.
- Chapter 6 presents the application of genetic algorithm (GA) in UC problem with various operating constraints, Also, we applied a crossover operator ring crossover for genetic algorithm (RCGA) to solve the UC problem, the results obtained show that, with the application of the proposed RCGA method to the unit commitment problem, better convergences and solutions are obtained than with the application of conventional genetic algorithm.
- Chapter 7 introduce a new method for optimization that is called root tree optimization algorithm (RTO), the robustness and efficiency of the proposed new method is validated on nonlinear functions and compared to recent methods addressing the same problem, simulation results confirm efficiency and reliability of the proposed RTO algorithm for solving complex optimization problem in term of solution quality and convergence characteristic. The proposed approach RTO has been applied to various test systems, from numerical results, it is found that the proposed RTO approach is able to provide better solution than other reported techniques in terms of fuel cost and time. Secondly, A new algorithm GAGE has been proposed to solve optimisation problems, which is inspired by the Genetic Engineering operation on the GA, the modified GAGE is efficiently applied to solve the UCP, the total production costs of GAGE over the scheduled period are less expensive than the conventional genetic algorithm and the algorithms proposed the recent literature.

The contributions of the dissertation along with the scope for future research in this area find a place in general conclusion.

CHAPTER I

Survey of research findings

I.1. Introduction :

Modem electric power systems built with nonlinear characteristics are highly interconnected with wide geographical distribution. This demands the optimization of a complex objective function under few practical constraints. Hence power system network optimization involves maximization or minimization of objective function under certain constraints [4].

The operation of a modem power system has to incorporate in its mission a strategy that serves to derive the maximum benefits of an improved performance and enhanced reliability [4]. The power grid networks have been analyzed using conventional and enumerative techniques for delivering the bulk power. reliably and economically, from power plants to the consumers. Though well-developed, these conventional approaches dealt with the local optima. Besides their limitations to handle mixed variables, these enumerative techniques have relied on special convergence properties and evaluation of auxiliary functions [5, 6].

The operations of energy management systems can be further optimized through optimization heuristic approach to the inherent issues, which govern the satisfactory delivery of electric power. It includes economic load dispatch, combined economic emission load dispatch and unit commitment problems.

The proposed work includes the state-of-the-art methods and procedures necessary for designing and developing an intelligence system. This work takes into account the theoretical investigations and practical considerations especially for mutual dependencies between intelligence and metaheuristic techniques such as GA, PSO, PS, BB-BC, ABC and their hybrid approaches.

I.2. Review Of Traditional Strategies :

Several mathematical optimization techniques have been proposed to solve the power system problems. In such an optimization problem, the main objective will be to minimize undesirable factors, such as cost, energy loss and errors, in order to maximize desirable factors, such as profit, quality and efficiency, subject to available limitations or constraints [4]. There are a wide range of mathematical programming techniques such as linear programming (LP)/interior point (IP) method, quadratic Programming (QP), nonlinear programming (NLP), decomposition technique, integer programming, mixed integer pogromming and dynamic programming (DP). This section attempts to review the basic concepts of these techniques.

I.2.1. Linear and Quadratic Programming Methods :

Linear programming (LP) methods have linear objective functions and constraints [7–9]. These methods basically fall into two categories: simplex and integer programming (IP) [10–17]. The main advantage of simplex method is its high computational efficiency. But the disadvantage is that number of iterations grows exponentially with problem size. This disadvantage can be overcome by IP methods.

IP methods do not step from one comer point to the next in the manner of simplex algorithm, but rather stay within the interior of the constrained region and progressively move to the optimal point. Both the simplex and IP methods can be extended to have a linear and quadratic objective function when the constraints are linear. Such methods are called quadratic programming (QP) [18–19]. LP has been used in various power system applications such as optimal power flow [S], load flow [8], reactive power planning [20], and active and reactive power dispatch [21–22].

I.2.2. Nonlinear Programming Methods :

In most of the NLP methods, the approach is to start from initial conditions and determine the 'descent direction' in which the value of objective function decreases for a minimization problem. A large number of NLP methods are available that are distinguishable by their definition and step length. Quasi-Newton method [23] that attempts to build up an approximation to Hessian matrix exhibits powerful convergence. If the coefficients of Hessian matrix are available analytically, Newton method [24] can be applied. Some of the most successful methods in use today are based on applying QP to solve a local optimization in a nonlinear problem. IP methods originally developed for LP can be applied to QP and NLP problems. NLP has been applied to solve optimal power flow [25] and hydrothermal scheduling [26] problems.

I.2.3. Integer and Mixed-Integer Programming Methods :

In cases where the independent variables can take only integer values, such problems are called integer programming. When some of the variables are continuous, the problem is called mixed integer programming. Mainly two approaches, namely 'branch and bound' and 'cutting plane methods', have been used to solve integer problems using mathematical programming techniques [23]. The size and complexity of integer and mixed-integer programmes that can be solved in practice depends on the structure of the problem. Integer/mixed integer programming have been applied to various areas of power systems such as optimal reactive power planning [27], power system planning [28–29], unit commitment [30] and generation scheduling [31].

I.2.4. Dynamic Programming Methods :

Dynamic programming (DP) based on the principle of optimality states that a sub-policy of an optimal policy must in itself be an optimal sub-policy. DP is a very powerful technique, but it suffers from the curse of dimensionality [32]. DP has been applied to various areas of power systems such as reactive power control [33], transmission planning [34] and unit commitment [35].

The main advantage of the intelligence based methods is that it avoids the complexities in the formulation of mathematical model for the power system optimization. However, the shortcoming of these methods is generally associated with the required excessive computational resources. With the advent of fast processors with large memory, these methods appear to be promising in the future [4] [36–40].

I.3. Literature Review :

They are reviewed in a systematic way in the following sections.

I.3.1. Economic Load Dispatch Problems :

I.3.1.1. *Economic Load Dispatch :*

The classical lambda iteration method has been used to solve the ELD problem. This method utilizes an equal incremental cost criterion for systems without transmission losses and the penalty factors using β, matrix for systems with transmission losses. Other methods such as gradient, Newton, linear programming and interior pint have also been applied to solve the ELD problems [41].

Zwe-Lee Gaing [42] has proposed a particle swarm optimization (PSO) method for solving the economic dispatch (ED) problem in power systems. This method made use of PSO for its global search capability to allocate optimum loading of each generator. The test results of three different systems have been compared with that of GA-based approach.

Jayabarathi et al. [43] have adopted a particle swarm optimization technique for solving the various types of economic dispatch problems. The test results of the sample systems have been compared with that of other evolutionary computing techniques.

I.3.1.2. *Combined Economic Emission Dispatch :*

Talaq et al. [44] have formulated an optimal power flow problem with emission constraints where the main objective was to minimize the fuel cost and the total emission over a wide time period of different intervals and system demands. The test results of standard 5-bus and IEEE-30 bus systems display a trade-off relationship between fuel cost and emission.

Wong et al. [45] have developed an efficient and reliable evolutionary-programming-based algorithm for solving the environmentally constrained economic dispatch (ECED) problem. This method made use of acceleration techniques in order to enhance the speed and robustness of the algorithm.

Venkatesh et al. [46] have built an EP algorithm to solve the CEED problem with line flow constraints. The line flows in MVA have been computed directly from the

Newton-Raphson method. A novel modified price penalty factor has been introduced to find the exact economic emission fuel cost with respect to the load demand. The test results of IEEE-14, -30 and -118 bus systems have been compared with that of other evolutionary computing techniques.

Abido [47] has derived a Pareto-based multi-objective evolutionary algorithm (MOEA) for solving an environmental/economic electric power dispatch problem.

This fuzzy-based hierarchical clustering technique has been implemented in order to obtain the best solution. The test results of an IEEE-30 bus system have been compared with that of other traditional multi-objective optimization techniques.

I.3.1.3. ***Economic Load Dispatch with Prohibited Operating Zones :***

Walters et al. [48] have developed a genetic algorithm to solve the economic dispatch problem with valve-point effects. This algorithm has utilized payoff information of the candidate solutions to evaluate their optimality. The test results of three units system have been compared with that of dynamic programming method.

Wong et al. [49] have built an incremental genetic algorithm based approach for the determination of global or near-global optimum solution. Another technique that incorporates both incremental genetic theory and simulated annealing has served to determine the economic loadings of 13 generators in a practical power system with the effects of valve-point loading and ramping characteristics. The test results have been found to yield better results when compared with that of simulated annealing based method.

Chen et al. [50] have presented a GA-based method that uses the incremental cost of encoded parameter of the system for solving the ED problem taking into account the network losses, ramp rate limits, valve-point zone and prohibited operating zone. The numerical results of the method for a large scale 40-unit system have been compared with that of lambda-iteration method.

Fung et al. [51] have formulated an integrated parallel genetic algorithm incorporating Tabu Search (TS) and simulated annealing for solving the ED problem.

The parallel computing platform has been based on a network of interconnected personal computers (PCs) using TCPAP socket communication facilities. The test results of a practical power system have been obtained to compute the optimal loading of 13 generators.

El-Gallad et al. [52] have adapted a PSO technique to solve the traditional economic dispatch problem. The objective function has been formulated as a combination of piecewise quadratic cost functions with non-differential regions, instead of adopting a single convex function for each generating unit. This innovation has served to incorporate practical operating conditions, such as valve-point effects and fuel types. The effectiveness of the algorithm has been tested on a three unit system and the results have been compared with that of a numerical method.

El-Gallad et al. [53] have added new constraints to the problem by introducing system spinning reserve and generator prohibited operating zones. In this formulation, they have included the same constraints but considered a single convex cost function [52]. The test results of a 15-unit system in which four units with prohibited operating zones have been compared with for both conventional method and the Hopfield neural network.

Lai et al. [54] have applied PSO to solve economic dispatch (ED) of units with non-smooth input-output characteristic functions. The test results of an IEEE-30 bus system with six generating units have been compared with that of evolutionary programming (EP).

Victoire et al. have extended Gaing's research by forming a hybrid optimizer to tackle the same problem [55]. They have used sequential quadratic programming to fine-tune the PSO search in finding the optimal solution. The feasibility has been illustrated by conducting case studies on a 10-unit system with valve-point effects for three different load-demand patterns and the results have been compared with that obtained using the EP-SQP method.

I.3.2. Unit Commitment :

Sheble et al. [56] have presented a genetic-based unit commitment (UC) scheduling algorithm. It has made use of GA with domain specific mutation operators for finding good unit commitment schedules. The test results of three different electric utilities have been compared with that of Lagrangian relaxation UC method.

Bakirtzis et al. [57] have developed a genetic algorithm that uses different quality function techniques to solve the unit commitment problem. The test results up to 100 generator units have been compared with that of dynamic programming and Lagrangian relaxation methods.

Swarup et al. [58] have employed a new solution methodology to the UC problem using genetic algorithm. The strategy has been found to be efficient and serve to handle larger size UC problems.

Zwe-Lee Gaing [59] has built an integrated approach of discrete binary particle swarm optimization (BPSO) with the lambda-iteration method for solving the UC problem. It has been solved as two sub problems using BPS0 method for minimization of the transition cost. The economic dispatch problem has been solved by lambda-iteration method for the minimization of the production cost. The feasibility of the method has been demonstrated on a 10- and a 26-unit systems, and the test results have been compared with that of GA method.

Zhao et al. [60] have presented an improved particle swarm optimization (IPSO) algorithm for power system UC problem. It has adopted an orthogonal design in order to generate the initial population that are scattered uniformly over a feasible solution space. The IPSO algorithm has been tested on a modeled 10-unit system and the performance is compared with that of GA and EP methods.

Ting et al. [61] have integrated a new approach of hybrid particle swarm optimization (HPSO) scheme, which is a blend of HPSO, BPSO and real-coded particle swarm optimization (RCPSO), to solve the UC problem. The UC problem has been handled by BPSO, whereas the economic load dispatch problem has been solved by RCPSO.

Funabashi et al. [62] have formulated a twofold simulated annealing method for the optimization of fuzzy-based UC model. The method has served to offer a robust solution for UC problem.

Victoire et al. [63] have applied a hybrid PSO and sequential quadratic programming (SQP) technique, prelude to tabu search (TS) method for solving the UC problem. The combinational part of the UC problem has been solved using the TS method. The nonlinear optimization part of economic dispatch problem (EDP) has been solved using a hybrid PSO-SQP technique. The effectiveness of hybrid optimization technique has been tested on a NTPS zone-II 7-unit system.

There have been various methods which are based on mathematical programming and metaheuristic-based for solving the thermal and hydrothermal UC problem in literature, these major methods are priority list, dynamic programming (DP), mixed-integer programming, heuristic unit, simulated annealing, tabu search, evolutionary programming, constraint logic programming, genetic algorithms, LR, interior point method, memetic algorithm, and neural network [64–71].

I.4. conclusion :

A detailed review of the existing methodologies in the field of power system scheduling has been carried out in this chapter. Several classical and heuristic methodologies adopted for the solution of scheduling problems have been looked at. Even though numerous solution methodologies exist, thinking of more efficient and computationally faster stochastic strategy is still relevant in the fourth chapter.

CHAPTER II

Mathematical formulation of the Economic Dispatch problem

II.1. Introduction :

The main aim of electric power utilities is to provide high-quality. reliable power supply to the consumers at the lowest possible cost while operating to meet the limits and constraints imposed on the generating units. This formulates the economic load dispatch (ELD) problem for finding the optimal combination of the output power of all the online generating units that minimizes the total fuel cost, while satisfying an equality constraint and a set of inequality constraints. As the cost of power generation is exorbitant, an optimum dispatch results in economy [1, 4].

In recent years, with an increasing awareness of the environmental pollution caused by thermal power plants, limiting the emission of pollutants is becoming a crucial issue in economic power dispatch. The conventional economic power dispatch cannot meet the environmental protection requirements, since it only considers minimizing the total fuel cost. The multi-objective generation dispatch in electric power systems treats economic and emission impact as competing objectives, which requires some reasonable tradeoff among objectives to reach an optimal solution. This formulates the combined economic emission dispatch (CEED) problem with an objective to dispatch the electric power considering both economic and environmental concerns [4].

Practically, the real world input/utput characteristics of the generating units are highly nonlinear, non-smooth and discrete in nature owing to prohibited operating zones, ramp rate limits and multi-fuel effects. Thus the resultant ELD is a challenging non-convex optimization problem, which is difficult to solve using traditional methods [1, 4].

In this chapter, we provide a mathematical formulation of the various types of economic load dispatch problems in power systems such as economic load dispatch (ELD), combined economic emission dispatch (CEED) and the economic load dispatch (ELD) with prohibited operating zones considering ramp rate limits.

II.2. Economic Load Dispatch Problem :

II.2.1. Problem Description :

ED is one of the important optimization problems in power system operations, which is used to determine the optimal combination of power outputs of all generating units to minimize the total fuel cost while satisfying various constraints over the entire dispatch periods [72].

The traditional or static ED problem assumes constant power to be supplied by a given set of units for a given time interval and attempts to minimize the cost of supplying this energy subject to constraints on the static behavior of the generating units like system load demand. Shortly, static ED determines the loads of generators in a system that will meet a power demand during a single scheduling period for the least cost [72–77].

II.2.2. Objective Function :

Economic load dispatch problem is the sub problem of optimal power flow (OPF). The main objective of ELD is to minimize the fuel cost while satisfying the load demand with transmission constraints [47].

The classical ELD with power balance and generation limit constraints has been formulated as follows.

$$\text{Minimize } F_t = \sum_{i=1}^{n} F_i(P_i) \tag{II.1}$$

$$F_i(P_i) = a_i + b_i P_i + c_i P_i^2 \tag{II.2}$$

Where F_t is the total fuel cost of generation,

$F_i(P_i)$ is the fuel cost function of i^{th} generator,

a_i, b_i, c_i are the cost coefficients of i^{th} generator,

P_i is the real power generation of i^{th} generator,

n represents the number of generators connected in the network

The minimum value of the above objective function has to be found by satisfying the constraints.

Therefore, it might fail to capture large variations of the load demand due to the ramp rate limits of the generators. Due to large variation of the customers load demand and the dynamic nature of the power systems, it became necessary to schedule the load beforehand so that the system can anticipate sudden changes in demand in the near future [77].

II.3. Dynamic Economic dispatch (ED) problem :

Dynamic ED is an extension of static ED to determine the generation schedule of the committed units so that to meet the predicted load demand over the entire dispatch periods at minimum operating cost under ramp rate and other constraints [73]. The ramp rate constraint is a dynamic constraint which used to maintain the life of the generators, i.e. plant operators, to avoid shortening the life of the generator, try to keep thermal stress within the turbines safe limits [74]. Since the violations of the ramp rate constraints are assessed by examining the generators output over a given time interval, this problem cannot be solved for a single value of MW generation [74]. The objective function of dynamic ED is formulated as follows

$$\text{Minimize } F_t(P) = \sum_{t=1}^{T}\sum_{i=1}^{N} F_i(P_i^t) \tag{II.3}$$

Where N is the set of committed units; P_i is the generation of unit i; $F_i(P_i)$ is the cost of producing P_i from unit i; T is the number of intervals in the study period. The fuel cost functions $F_i(\cdot)$ is derived from the fuel consumption function.

The dynamic ED is not only the most accurate formulation of the economic dispatch problem but also the most difficult to solve because of its large dimensionality [75]. The DED problem is normally solved by discretization of the entire dispatch period into a number of small time intervals, over which the load demand is assumed to be constant and the system is considered to be in a temporal steady state. Over each time interval a static ED problem is solved under static constraints and the ramp rate constraints are enforced between the consecutive intervals [76]. In the DED problem the optimization is done with respect to the dispatchable powers of the units.

Some researchers have considered the ramp rate constraints by solving SED problem interval by interval and enforcing the ramp rate constraints from one interval to the next.

However, this approach can lead to suboptimal solutions; moreover, it does not have the look-ahead capability [77].

Since dynamic ED was introduced, various methods have been used to solve this problem. However, all of those methods may not be able to provide an optimal solution and usually getting stuck at a local optimal.

II.4. ED Constraints :

The constrained ED problem is subjected to a variety of constraints depending upon assumptions and practical implications. Usually, formulation of ED problem includes such constraints as load generation balance, minimum and maximum capacity constraints. To maintain system reliability and security, spinning reserve constraints and security constraints can be added to the dynamic ED problem. The inclusion of the prohibited zones, ramp-rate limits and other practical constraints results in no-convex ED of generating units. All these constraints are discussed below [77].

II.4.1. Load-Generation Balance :

The generated power from all the running units must satisfy the load demand and the system losses given by (II-4)

$$\sum_{i=1}^{N} P_i^t = P_D^t + P_L^t, \qquad \mathrm{t} = 1, 2, ..., \mathrm{T} \tag{II.4}$$

where P_D^t is the demand and P_L^t is the system transmission loss. Their sum represents the effective load to be satisfied at the t^{th} interval. The transmission line losses can be expressed in terms of the unit outputs:

$$P_L^t = \sum_{i=1}^{n} \sum_{j=1}^{n} P_i^t \beta_{ij} P_j^t + \sum_{i=1}^{n} \beta_{io} P_i^t + \beta_{oo} \tag{II.5}$$

where β_{ij} is the ij^{th} element of the loss coefficient square matrix, β_{i0} is the i^{th} element of the loss coefficient, and B_{00} is the constant loss coefficient. Sometimes the last two terms are omitted.

In a competitive environment, the load-generation balance constraint is relaxed and each generating company schedules its production to maximize its profits given a forecast of electricity prices for the scheduling period [77]. As a first approximation, each generating unit could be optimized separately in this problem because of the decoupling made possible by the availability of prices at each period. Dynamic constraints (such as ramp rates and minimum up and down time constraints) complicate the problem because a generating company that owns a portfolio of units must then decide whether to buy “flexibility” on the market or meet the dynamic constraints with its own resources [78].

II.4.2. Generation Capacity Constraint :

For normal system operations, real power output of each generator is restricted by lower and upper bounds as follows:

$$P_i^t + S_i^t \le P_i^{\max} \quad i = 1, 2, ..., N, \quad t = 1, 2, ..., T \tag{II.6}$$

$$P_i^{\min} \le P_i^t \quad i = 1, 2, ..., N, \quad t = 1, 2, ..., T \tag{II.7}$$

Where $P_i^{\min}$ and $P_i^{\max}$ are the minimum and maximum power produced by generator i, S_i^t is the reserve contribution of unit during time interval t.

II.4.3. Generating Unit Ramp Rate Limits :

One of unpractical assumption that prevailed for simplifying the problem in many of the earlier research is that the adjustments of the power output are instantaneous [79]. Therefore, the power output of a practical generator cannot be adjusted instantaneously without limits. The operating range of all online units is restricted by their ramp-rate limits during each dispatch period. So, the subsequent dispatch output of a generator should be limited between the constraints of up and down ramp-rates [80] as follows

The power generated, P_i^t, by the ith generator in certain interval may not exceed that of previous interval by P_i^{t-1} more than a certain amount UR_i, the up-ramp limit and neither may it be less than that of the previous interval by more than some amount DR_i the down-ramp limit of the generator. These give rise to the following constraints.

Generating unit ramp-rate limits:

$$\begin{aligned} P_i^t - P_i^{t-1} &\le UR_i, i = 1, 2, ..., N \\ P_i^{t-1} - P_i^t &\le DR_i, i = 1, 2, ..., N \end{aligned} \tag{II.8}$$

Where UR_i and DR_i are ramp-up and ramp-down rate limits of i^{th} unit, respectively and are expressed in MW/h.

II.4.4. Reserve Contribution :

The maximum reserve contribution has to satisfy following constraints:

$$0 \le S_i^t \le S_i^{\max} \quad i = 1, 2, ..., N, \quad t = 1, 2, ..., T \tag{II.9}$$

Where $S_i^{\max}$ is the maximum contribution of unit i to the reserve capacity.

Maximum-ramp spinning reserve contribution is defined as in (II.10)

$$0 \le S_i^t \le UR_i .\Delta t \qquad i = 1, 2, ..., N, \quad t = 1, 2, ..., T \tag{II.10}$$

Where S_i^{t} is the spinning reserve of unit i .

II.4.5. System Spinning Reserve Requirement :

Sufficient spinning reserve is required from all running units to maximize and maintain system reliability [31]. There are many ways to determine the system spinning reserve requirement. It can be calculated as the size of the largest unit in operation or as a percentage of forecast load demand or even as a function of the probability of not having sufficient generation to meet the load [73]. The spinning reserve can be defined by (II.11)

$$\sum_{i=1}^{N} S_i^t \ge SR^t \qquad t = 1, 2, ..., T \tag{II.11}$$

Where SR^t is the system spinning reserve requirement for time interval t.

II.4.6. Tie-line Limits :

The economic dispatch problem can be extended by importing additional constraint like transmission line capacity limit given by (II.12)

$$P_{Tjk,\min} \le P_{Tjk} + S_{jk} \le P_{Tjk,\max} \tag{II.12}$$

Where $P_{T_{jk,min}}$ and $P_{T_{jk,max}}$ specify the tie-line transmission capability, i.e. the transfer from area j to area k should not exceed the tie-line transfer capacities for security consideration. Each area has own special load and its spinning reserve [81–82].

II.4.7. Prohibited Zone :

The generating units may have certain ranges where operation is restricted on the grounds of physical limitations of machine components or instability, e.g. due to steam valve or vibration in shaft bearings. So, there is a quest to avoid operation in these zones in order to economize the production [79]. These ranges are prohibited from operation and a generator with prohibited regions (zones) has discontinuous fuel-cost characteristics (Fig.II.1) [83]. The acceptable operating zones of a generating unit can be formulated as follows

$$P_i^{\min} \le P_i^t \le P_{i,1}^l \qquad \text{(II.13)}$$

$$P_{i,j-1}^u \le P_i^t \le P_{i,j}^l \qquad i \in \theta,\ j=2, 3, \ldots, n_i.\ t=1, 2, \ldots, T \qquad \text{(II.14)}$$

$$P_{i,nj}^u \le P_i^t \le P_i^{\max} \qquad \text{(II.15)}$$

Where n_i is the number of the prohibited zones in unit i, θ is the set of units that have prohibited zones, $P_{i,j}^l$, $P_{i,j}^u$ are the lower and upper bounds of the j^{th} prohibited zone.

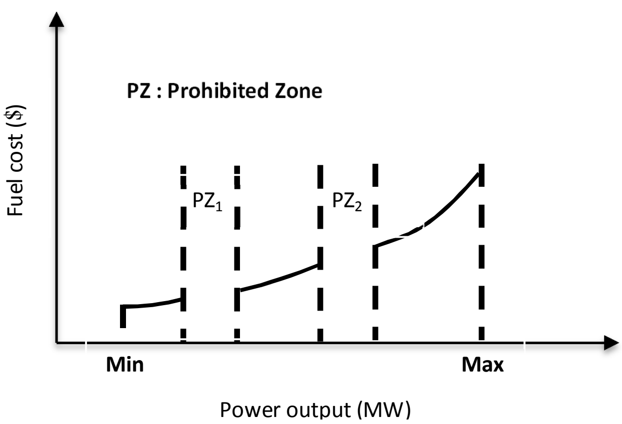


Figure II.1 : *Example of cost function with two prohibited operating zones*

II.5. Different Objective Functions :

The dynamic ED problem has been solved with many different forms of the cost function, such as the smooth quadratic cost function (II.16) or the non-smooth cost function due to the valve-point effects (II.17). Also, a linear cost function [74] and piecewise linear cost function [84, 85] have been employed. For smooth cost function it is usually assumed that its incremental cost function. In some power systems combined cycle units are used to supply the base load. For these units the cost function can be given as linear, piecewise or quadratic with decreasing incremental cost function [85].

For units with prohibited zones, the fuel cost function is discontinuous and non-convex. An interesting departure from this standard formulation is the approach proposed by Wang and Shahidehpour [86] who include in the objective function a term representing the reduction in the life of the turbine caused by excessive ramping rates. This flexible technique makes possible a tradeoff between the system operating cost and the life cycle cost of the generating units [78].

II.5.1. Smooth Cost Function :

The most simplified cost function of each generator can be represented as a quadratic function as given in (II.16) whose solution can be obtained by the conventional mathematical methods

$$C_i(P_i^t) = a_i + b_i P_i^t + c_i.(P_i^t)^2 \tag{II.16}$$

Where a_i, b_i, c_i are cost coefficients of generator *i*.

II.5.2. Non-smooth Cost Functions with Valve-point Effects :

The generating units with multi-valve steam turbines exhibit a greater variation in the fuel cost functions because in order to meet the increased demand a generator with multi-valve steam turbines increase its output and various steam valves are to be opened [72].

This valve-opening process produces ripple like effect in the heat-rate curve of the generator. The inclusion of valve-point loading effects makes the modeling of the incremental fuel cost function of the generators more practical [87].

Therefore, in reality, the objective function of ED problem has non-differentiable property.

Consequently, the objective function should be composed of a set of non-smooth cost functions. Considering non-smooth cost functions of generation units with valve-point effects, the objective function is generally described as the superposition of sinusoidal functions and quadratic functions [88].

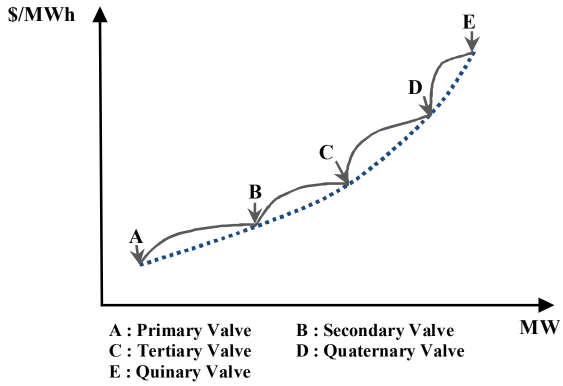


Figure II.2 : *Cost function with valve-point effects*

$$C_i(P_i^t) = a_i + b_i P_i^t + c_i (P_i^t)^2 + \left| e_i . \sin(h_i (P_i^{\min} - P_i^t)) \right| \tag{II.16}$$

Where e_i and h_i are the coefficients of generator i reflecting valve point effects. As shown in Fig. II.2, this increases the non-linearity of curve as well as number of local optima in the solution space [87] compared with the smooth cost function due to the valve point effects. Also the solution procedure can easily trap in the local optima in the vicinity of optimal value.

II.5.3. Non-smooth Cost Functions with Multiple Fuels :

Since the dispatching units are practically supplied with multi-fuel sources, each unit should be represented with several piecewise quadratic functions reflecting the effects of fuel type changes, and the generator must identify the most economic fuel to burn. The resulting cost function is called a “hybrid cost function.” Each segment of the hybrid cost function implies some information about the fuel being burned or the units operation [77].

Thus, generally, the fuel cost function is a piecewise quadratic function described as follows

$$C_i(P_i^t) = \begin{cases} a_{i1} + b_{i1} P_i^t + c_{i1} (P_i^t)^2 & \text{if} \quad P_{i,\min}^t \le P_i^t \le P_{i,1}^t \\ a_{i2} + b_{i2} P_i^t + c_{i2} (P_i^t)^2 & \text{if} \quad P_{i,1}^t \le P_i^t \le P_{i,2}^t \\ \vdots & \qquad \vdots \\ a_{in} + b_{in} P_i^t + c_{in} (P_i^t)^2 & \text{if} \quad P_{i,n-1}^t \le P_i^t \le P_{i,\max}^t \end{cases} \tag{II.17}$$

Where are a_{ip}, b_{ip}, c_{ip} the cost coefficients of generator for the p^{th} power level. The incremental cost functions are illustrated in Fig. II.3.

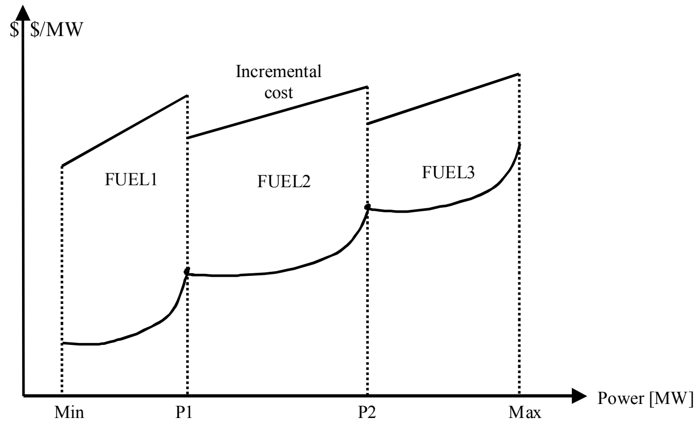


Figure II.3 : *Cost function with multiple fuels*

II.5.4. Non-smooth Cost Functions with Valve-Point Effects and Multiple Fuels :

To obtain an accurate and practical economic dispatch solution, the realistic operation of the ED problem should consider both valve-point effects and multiple fuels. The reference [89] proposed an incorporated cost model, which combines the valve-point loadings and the fuel changes into one frame. Therefore, the cost function should combine (2–17) with (2–18), and can be realistically represented as shown in (II.18)

$$C_i(P_i^t) = \begin{cases} a_{i1} + b_{i1}P_i^t + c_{i1}(P_i^t)^2 + \left|e_{i1}.\sin(h_{i1}(P_{i,1}^{\min} - P_i^t))\right| & \text{if } P_{i,\min}^t \le P_i^t \le P_{i,1}^t \\ a_{i2} + b_{i2}P_i^t + c_{i2}(P_i^t)^2 + \left|e_{i2}.\sin(h_{i2}(P_{i,2}^{\min} - P_i^t))\right| & \text{if } P_{i,1}^t \le P_i^t \le P_{i,2}^t \\ \vdots & \vdots \\ a_{in} + b_{in}P_i^t + c_{in}(P_i^t)^2 + \left|e_{in}.\sin(h_{in}(P_{i,n}^{\min} - P_i^t))\right| & \text{if } P_{i,n-1}^t \le P_i^t \le P_{i,\max}^t \end{cases} \tag{II.18}$$

II.5.5. Emission Function :

Due to increasing concern over the environmental considerations, society demands adequate and secure electricity, i.e. not only at the cheapest possible price, but also at minimum level of pollution. In this case, two conflicting objectives, i.e., operational costs and pollutant emissions, should be minimized simultaneously [90–92]. The atmospheric pollutants such as sulphur oxides (SO_x) and nitrogen oxides (NO_x) caused by fossil-fueled generating units can be modeled separately or as the total emission of them which is the sum of a quadratic [90] and an exponential function and can be expressed as

$$\sum_{t=1}^{T}\sum_{i=1}^{N} \beta_i + \beta_i P_i^t + \gamma_i (P_i^t)^2 + \eta_i \exp(\delta_i P_i^t) \tag{II.19}$$

Where α_i, β_i, γ_i, η_i and δ_i are emission coefficients of i^{th} generating unit.

II.6. Traditional approaches :

II.6.1. The Lambda –Iteration Method :

In Lambda iteration method lambda (λ) is the variable introduced in solving constraint optimization problem and is called Lagrange multiplier. It is important to note that lambda can be solved at hand by solving systems of equation. Since all the inequality constraints to be satisfied in each trial the equations are solved by the iterative method [91],

i) Assume a suitable value of $\lambda^{(0)}$ this value should be more than the largest intercept of the incremental cost characteristic of the various generators,

ii) Compute the individual generations,

iii) Check the equality,

$$P_d = \sum_{i=1}^{N} P_i \quad \text{is satisfied} \tag{II.20}$$

iv) If not, make the second guess λ repeat above steps.

II.6.2. The Gradient Search Method :

This method works on the principle that the minimum of a function, *f(x)*, can be found by a series of steps that always take us in a downward direction. From any starting point, x^0, we may find the direction of "steepest descent" by noting that the gradient *f*, [91]

$$\nabla f = \begin{bmatrix} \dfrac{\partial f}{\partial x_1} \\ \vdots \\ \dfrac{\partial f}{\partial x_n} \end{bmatrix}$$

Always points in the direction of maximum ascent. Therefore, if we want to move in the direction of maximum descent, we negate the gradient. Then we should go from x^0 to x^1 using:

$$x^1 = x^0 - \nabla f \alpha \tag{II.21}$$

Where α is a scalar to allow us to guarantee that the process of convergence. The best value of α must be determined by experiment. In case of power system economic load dispatch f becomes

$$f = \sum_{i=1}^{N} F_i(P_i) \tag{II.22}$$

The object is to drive the function to its minimum. However we have to be concerned with the constraints function

$$\phi = (P_{Laod} - \sum_{i=1}^{N} P_i) \tag{II.23}$$

To solve the economic load dispatch problem which involves minimizing the objective function and keeping the equality constraints, we must apply the gradient technique directly to the Lagrange function is:

$$\Im = \sum_{i=1}^{N} Fi(P_i) + \lambda(P_{Load} - \sum_{i=1}^{N} P_i) \tag{II.24}$$

And the gradient of this function is

$$\nabla\Im = \begin{bmatrix} \dfrac{\partial\Im}{\partial P_1} \\ \vdots \\ \dfrac{\partial\Im}{\partial P_n} \end{bmatrix}$$

The problem with the formulation is the lack of a guarantee that the new points generated each step will lie on the surface ϕ.

The economic dispatch algorithm requires a starting λ value and starting values for P_1, P_2, and P_3.The gradient for $\Im$ is calculated as above and the new values of λ, P_1,and P_2 etc., are found from

$$x^1 = x^0 - (\nabla\Im)\alpha \tag{II.25}$$

Where x is a vector, $x = \begin{bmatrix} P_1 \\ P_2 \\ \vdots \\ \lambda \\ \end{bmatrix}$

II.6.3. Newton's Method:

Newton's method goes a step beyond the simple gradient method and tries to solve the economic dispatch by observing that the aim is to always drive, [91]

$$\nabla \Psi x = 0$$

Since this is a vector function, we can formulate the problem as one of finding the correction that exactly drives the gradient to zero (i.e. to a vector, all of whose elements are zero). Suppose we wish to drive the function $g(x)$ to zero. The function g is a vector and the unknown, x are also vectors. Then to use Newton's method, we observe

$$g(x+\Delta x) = g(x) + \left[g'(x)\right]\Delta x = 0 \qquad \text{(II.26)}$$

Where $g'(x)$ is the familiar Jacobian matrix. The adjustment at each step is then,

$$\Delta X = -\left[g'(x)\right]^{-1} g(x) \qquad \text{(II.27)}$$

Now, if we let the g function be the gradient vector $\nabla \Psi x$ we get

$$\Delta X = -\left[\frac{\partial}{\partial x}\nabla \Psi_x\right]^{-1} \nabla \Psi \qquad \text{(II.28)}$$

For the economic load dispatch problem this takes the form:

$$\Psi = \sum_{i=1}^{N} F_i(P_i) + \lambda\left(P_{Load} - \sum_{i=1}^{N} P_i\right) \qquad \text{(II.29)}$$

The $\nabla \psi_x$ is a Jacobean matrix which has now second order derivatives is called Hessian matrix. Generally, Newton's method will solve for the correction that is much closer to the minimum generation cost in one cost in one step than would the gradient method [91].

II.6.4. Economic Dispatch with piecewise linear cost functions :

In this method economic load dispatch problem of those generators are solved whose cost functions are represented as single or multiple segment linear cost functions. Here for all units running, we start with all of them at P_{min}, then begin to raise the output of the unit with the lowest incremental cost segment. If this unit hits the right-hand end of a segment, or if it hits P_{max}, we then find the unit with the next lowest incremental cost segment and raise its output [91, 64].

Eventually, we will reach a point where a units output is being raised and the total of all unit outputs equal the load, or load plus losses. At that point, we assign the last unit being adjusted to have a generation which is practically loaded for one segment. to make this procedure very fast, we can create a table giving each segment of each unit its MW contribution. Then we order this table by ascending order of incremental cost. By search in from the top down in this table we do not have to go and look for the next segment each time a new segment is to be chosen. This is an extremely fast form of economic dispatch [91].

II.6.5. Base Point and Participation Factor :

This method assumes that the economic dispatch problem has to be solved repeatedly by moving the generators from one economically optimum schedule to another as the load changes by a reasonably small amount. It is started from a given schedule called the base point . next assumes a load change and investigates how much each generating unit needs to be moved in order that the new load served at the most economic operating point [91].

II.6.6. Linear Programming :

Linear programming (LP) is a technique for optimization of a linear objective function subject to linear equality and linear in-equality constraints. Informally, linear programming determines the way to achieve the best outcome (such as maximum profit or lowest cost) in a given mathematical model and given some list of requirements represented as linear equations. For example if f is function defined as follows [91, 64].

$$f(x_1, x_2, ..., x_n) = c_1x_1 + c_2x_2 + ... + c_nx_n + d \qquad \text{(II.30)}$$

A linear programming method will find a point in the optimization surface where this function has the smallest (or largest) value. Such points may not exist, but if they do, searching through the optimization surface vertices is guaranteed to find at least one of them. Linear programs are problems that can be expressed in canonical form,

$$\begin{aligned} &\text{Maximize} \quad C^T X \\ &\text{Subject to} \quad AX \le b \end{aligned}$$

X represents the vector of variables (to be determined), while C and b are vectors of (known) coefficients and A is a (known) matrix of coefficients. The expression to be maximized or minimized is called the objective function (C^T in this case). The equations $AX \leq b$ are the constraints which specify a convex polyhedron over which the objective function is to be optimized.

II.6.7. Dynamic Programming :

When cost functions are no-convex equal incremental cost methodology cannot be applied [64].

Under such circumstances, there is a way to find an optimum dispatch which use dynamic programming method. In dynamic Programming is an optimization technique that transforms a maximization (or minimization) problem involving n decision variables into n problems having only one decision variable each. This is done by defining a sequence of Value functions V_1, V_2 , ... V_n, with an argument y representing the state of the system. The definition of $V_i(y)$ is the maximum obtainable if decisions 1, 2 ...I are available and the state of the system is y. The function V_1 is easy to find. For I=2,...n, V_i at any state y is calculated from V_{i-1} by maximizing, over the I^{th} decision a simple function (usually the sum) of the gain of decision i and the function V_{i-1} at the new state of the system if this decision is made. Since V_{i-1} has already been calculated, for the needed states, the above operation yields V_i for all the needed states. Finally, V_n at the initial state of the system is the value of the optimal solution. The optimal values of the decision variables can be recovered, one by one, by tracking back the calculations already performed [91, 64].

II.7. Optimal Power Flow :

It is very clear from previous section that transmission loss bias the economic dispatch problem and the coordination equations include the effects of incremental transmission loss and increased the complexity of problem. Behavior of network elements leads many effects on system operation. For instance, when network transmission lines are considered in formulation, it indicates some of the effects like increase in the total generation demand due to real power losses, adjustments in the generation schedule in accordance to the limits on transmission line flows. Thus, it is very important to take into account the effects of network elements in finding the optimal solution to ensure system security [92–98].

Optimal power flow (OPF) is an extension to conventional ED problem; it determines minimal cost by optimal settings of different control variables in the system [98]. The OPF is a power flow problem in which certain controllable variables are adjusted to optimize system objectives. Some of the objective functions which are optimized using OPF formulation are the cost of active power generation, system losses, emission of generating units etc., while satisfying power flow equations, equipment operation limits and system security. The controls that an OPF can accommodate are active and reactive power injections, generator voltages, transformer tap ratios and phase shifter angles [91-94].

OPF is very different from ordinary power flow. In power flow calculation the objective is to find bus voltage magnitudes and phase angles at all the buses in the system [98].

Power flow is a steady state study and gives the snap shot of the whole system operating state. It is given with scheduled complex loads on all load buses and generated active powers, voltage magnitudes on all generator buses. The net flow of power from a bus into the system is termed as injection at that bus. Power flow finds the load bus voltage magnitudes and phase angles by minimizing the difference between scheduled injection and calculated injections using techniques like Gauss-Seidal or Newton-Raphson. Scheduled injection at a bus is the difference between scheduled power generation if any and the complex load at that particular bus. The power injections at a bus are derived in the next section and calculated using equations (II.40) and (II.42). Post power flow calculations are carried out by system operators using the bus voltage magnitudes and corresponding phase angles to find the current state of the system. These calculations involve line power flows, line losses and reactive power generation at generator buses. Power system operators have to plan the adjustments accordingly if these values exceed their corresponding limits to ensure system's secure operation [98].

Optimal power flow is a very large and complex mathematical problem. In general OPF is posed as minimizing the function $F(x,u)$ while satisfying nonlinear equality constraints $g(x,u) = 0$ and nonlinear inequality constraints $h(x,u) \leq 0$ on the vectors x and u.

The vector x contains dependent variables including bus voltage magnitudes and phase angles and the reactive power outputs of generators on voltage controlled buses. The vector u consists of control variables which are independent and involves active and reactive power generations, transformer phase shifter angles, transformer tap ratio settings, load shedding, DC line flow, switched capacitor settings.

OPF problem with the objective function of minimizing the generation cost in thermal electric power system is discussed here. In the ED solution presented so far, limits on only minimum and maximum active power generations are observed. In OPF many more limits on power systems equipment's can be included like bounds on reactive power generations, transmission line flows, bus voltage magnitudes. OPF problem finds an optimal profile of active and reactive power generations along with voltage magnitudes in such a manner as to minimize the total operating costs [98].

The objective function is same as the one shown in equations (II.1) and (II.2), whereas the list of constraints subjected to

1. Power Balance in the network.
2. Unit generation limits.
3. Limits on load bus voltage magnitudes.
4. Limits on transmission line flows, transformer tap settings and phase shifter angles.

Objective function: The sum of fuel cost of all committed generators is to be minimized,

Subjected to: Active and reactive power balance in the network,

$$Pg_i - Pd_i - P_i = 0, \quad i = 1, 2, ..., N \tag{II.31}$$

$$Qg_i - Qd_i - Q_i = 0, \quad i = 1, 2, ..., Nb \tag{II.32}$$

Where Pg_i, Qg_i represents active and reactive power generations P_i, Q_i represents active and reactive power injections at bus i and Pd_i, Qd_i represents active and reactive power demands at bus i, N is total number of buses and Nb is total number of load buses in the system.

Limits on active and reactive power generations on all generator buses:

$$Pg_{i,\min} \le Pg_i \le Pg_{i,\max}, \quad i = 1, 2, ..., ng \tag{II.33}$$

$$Qg_{i,\min} \le Qg_i \le Qg_{i,\max}, \quad i = 1, 2, ..., ng \tag{II.34}$$

Limits on voltage magnitudes and phase angles on all load buses:

$$V_{i,\min} \le V_i \le V_{i,\max}, \quad i = 1, 2, ..., Nb \tag{II.35}$$

$$\delta_{i,\min} \le \delta_i \le \delta_{i,\max}, \quad i = 1, 2, ..., Nb \tag{II.36}$$

Limits on line flows can be expressed either in MW, Amperes or MVA, if it is expressed in MW then:

$$P_{ij,\min} \le P_{ij} \le P_{ij,\max}, \quad i = 1, 2, ..., Nl \tag{II.37}$$

Where P_{ij} is the active power flow between buses i and j. $P_{ij,min}$, $P_{ij,max}$ are corresponding minimum and maximum limits, Nl is the total number of transmission lines.

The constraint optimization problem can be transformed into an unconstrained one by augmenting the equality constraints of active and reactive power balance equations into the objective function using Lagrange multipliers. The solution of this Lagrangian function involves first order and second order partial derivates terms called the Jacobian and Hessian matrices respectively. The complete solution of OPF using Hessian matrix by Newton's method is presented in [94].

II.7.1. Calculation of Bus Injections :

The calculation the power injection at a bus requires basic power equation and the admittance matrix Y. Apparent power at any node in the network is given by [98]

$$S_i = V_i I_i^* = P_i + jQ_i$$

Where S_i is the apparent power, V_i is the complex voltage and I_i is the complex current at bus i And '*' represents complex conjugate.

For simplicity in calculations the above equation is rewritten as

$$S_i^* = V_i^* I_i = P_i - jQ_i \tag{II.38}$$

Where I_i is the current flowing out at bus i, and is given as the sum of all the currents leaving the bus. Using πequivalent model of transmission lines, it can be obtained as

$$I_i = \sum_{j=1}^{N} Y_{ij} V_i \tag{II.39}$$

Y_{ij} represents (i, j) element in the network admittance matrix, can be written in conductance (G) and suseptance (B) form as $Y_{ij} = \mathrm{G}_{ij} + \mathrm{jB}_{ij}$. Thus,

$$P_i - jQ_i = V_i \angle - \delta_i \left(\sum_{j=1}^{N} (G_{ij} + jB_{ij}) V_i \right)$$

On separating real and imaginary parts

$$P_i = |V_i| \sum_{j=1}^{N} |V_j| (G_{ij} \cos(\delta_i - \delta_j) + B_{ij} \sin(\delta_i - \delta_j)) \tag{II.40}$$

$$Q_i = |V_i| \sum_{j=1}^{N} |V_j| (G_{ij} \sin(\delta_i - \delta_j) + B_{ij} \cos(\delta_i - \delta_j)) \tag{II.41}$$

Equation (I.40) and (II.41) represents real and reactive power injections respectively at bus i.

II.7.2. Calculation of Line Flows

Consider the π representation of a line connecting buses i and j shown in the Fig. II.4. The figure shows the bus i to be the transformer side bus, with the ratio 1: a . Hence, $V_t = aV_i$. The representation has a series admittance, y_{ij} and shunt admittances, y_{Si} and y_{Sj} at the ends of the line. The power from the bus i to bus j can thus be given as [98]

$$S_{ij} = P_{ij} + jQ_{ij} = (aV_i)(I_i)^*$$
$$S_{ij}^* = P_{ij} - jQ_{ij} = (aV_i)^* I_i$$

And

$$I_i = I_{ij} + I_{Si}$$
$$I_i = (aV_i - V_j) y_{ij} + (aV_i) y_{Si}$$

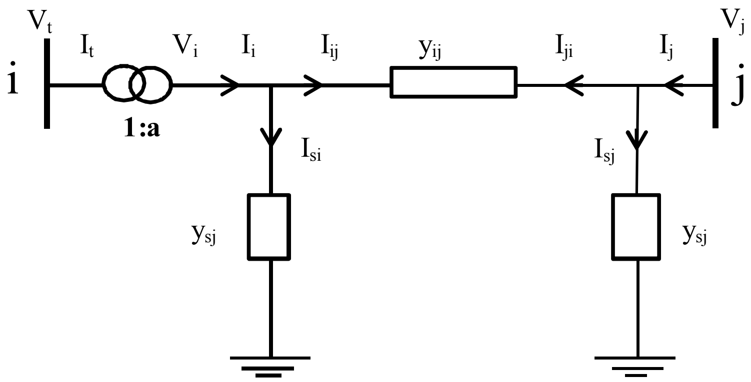


Figure II.4 : *Transmission Line π Model.*

In polar form the equation becomes

$$P_{ij} - jQ_{ij} = aV_i\angle -\delta_i((aV_i\angle -\delta_i - V_j\angle -\delta_j)(g_{ij} - jb_{ij}) + aV_i\angle\delta_i(g_{Si} - jb_{Si}))$$

On separating real and imaginary parts we arrive at the active and reactive power flows in the Line

$$P_{ij} = a^2|V_i|^2(gs_i + g_{ij}) - a|V_i||V_j|(g_{ij}\sin(\delta_i - \delta_j) + b_{ij}\sin(\delta_i - \delta_j)) \quad \text{(II.42)}$$

$$Q_{ij} = -a^2|V_i|^2(bs_i + b_{ij}) - a|V_i||V_j|(g_{ij}\sin(\delta_i - \delta_j) + b_{ij}\sin(\delta_i - \delta_j)) \quad \text{(II.43)}$$

II.8. conclusion :

The optimum load dispatch of power system is discussed in this chapter. When the problem is to be solved few constraints has to be kept in mind. Various objectives and different types of constraints are discussed in this chapter. Various traditional methods applied to solve the economic load dispatch problem is also discussed.

The generalized formulation of the OPF problem is expressed and the OPF formulation is presented and various constraints are discussed.

CHAPTER III

The Unit Commitment (UC) problem formulation

III.1. Introduction :

Economic operation of power system is very important to return profit on the capital invested and to subside a part of investment itself through proper planning. More significantly it is important from the perspective of conserving the irreplaceable fossil fuels [98].

Economic operation results in maximizing the operating efficiencies which in turn minimize the cost per kilowatt-hour. Total load on power system varies at every instant of time, generally being higher during the daytime and early evening when industrial loads are high, lights are on, and so forth, and lower during the late evening and early morning when most of the population is asleep. In addition, the use of electric power has a weekly cycle, the load being lower over weekend days than weekdays. Therefore, the option of turning ON enough units and leave them online, so that the variable load demand is met at all times is not viable due to the costs involved. This causes some of the units to operate near their minimum capacity at times, resulting in lower system efficiency and increased economics. Thus, if the operation of the system is to be optimized, units must be shut down as the load goes down and must be brought online as it goes up again [95].

Electric utilities have to plan their generation to meet this varying load in advance, as to which among their available generators are to start-up and when to synchronize them into the network as well as the sequence in which the operating units must be shut down. The process of making this decision is well known as ‘Unit Commitment’. The word ‘commit’ refers to ‘turn ON’ a unit. Thus, the problem of Unit Commitment is to schedule the ON and OFF times of the generating units with the overall minimum cost while ensuring the unit’s operational constraints like minimum up/downtimes, ramp rate limits, maximum and minimum power generation limits [91, 96].

Out of the cost incurred in generation, major component is the cost of fuel input per hour for all the generators, while maintenance cost contributes only to a small extent. This fuel cost evaluation is more important for thermal and nuclear power stations, which is not the case with hydro stations where the energy is obtained from storing water in dams built for irrigation purpose and is apparently free. Fuel cost savings can be obtained by proper allocation of load among the committed units. But the problem of UC minimizes the total cost which includes both production cost i.e., the fuel cost and costs associated with the start-up and shutdown of units. Start-up cost and shutdown cost are categorized by unit type. A fixed cost is incurred with the shut-down of a unit while the start-up cost is dependent on the length of time the unit has been down prior to starting. When performing the unit commitment scheduling a variety of operating constraints and spinning reserve requirements are observed [91, 96].

The Unit Commitment (UC) is an important research challenge and vital optimization task in the daily operational planning of modern power systems due to its combinatorial nature. Because the total load of the power system varies throughout the day and reaches a different peak value from one day to another, the electric utility has to decide in advance which generators to start up and when to connect them to the network and the sequence in which the operating units should be shut down and for how long. The computational procedure for making such decisions is called unit commitment, and a unit when scheduled for connection to the system is said to be committed. In this work the commitment of fossil-fuel units has been considered which have different production costs because of their dissimilar efficiencies, designs, and fuel types. Unit commitment plans for the best set of units to be available to supply the predict forecast load of the system over a future time period [98].

In general, the UC problem may be formulated as a non-linear, large scale, mixed-integer combinatorial optimization problem with both binary (unit status variable) and continuous (unit output power) variables. This chapter presents the characteristics of power generation unit, unit commitment problem formulation, modeling aspects of single approaches to solve UCP.

III.2. Generator characteristics :

Fundamental constituent in economic operation of a unit is its performance characteristics, which depicts the relation between input and output. This characteristics specifies the input energy rate or cost of fuel used per hour as a function of generator power output. The input-output characteristic of a generating unit is obtained by combining directly the input-output characteristics of boiler and that of turbine-generator set [91]. A typical input-output characteristic also called fuel cost curve of a thermal generating unit is convex as shown in Fig. III.1.

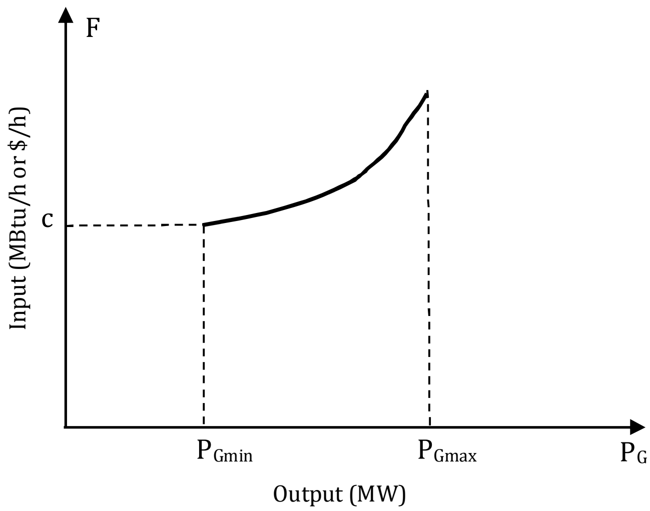


Figure III.1: *Input-Output Characteristics of a Thermal Generator*

It can be seen that the characteristics are bounded between minimum and maximum capacities. The minimum power output limitations are generally caused by boiler's fuel combustion stability and design [91] whereas maximum limit is determined by the design capacity of boiler, turbine, generator. These non-linear characteristics are generally approximated to a quadratic function expressed in terms of unit's power generation as shown in eq. (II.1 and II.2).

III.3. Start-up and shut down costs :

As mentioned earlier there exists a cost incurred in starting and shutting down a unit, apart from fuel cost. Certain amount of energy must be expended to bring a unit online because the temperature and pressure of the thermal unit must build slowly. This energy does not result in any MW power output and is considered as start-up cost. There are two types of start-up costs called hot start-up cost and cold start-up cost. If the unit's boiler is allowed to cool down and then heat back up to operating temperature while turning ON the unit it is called cooling and the corresponding cost is cold start cost. On the other hand if the boiler is supplied with sufficient energy to just maintain operating temperature until the unit is brought online again is called as banking and the cost involved is called hot start cost. This hot start cost varies directly with the duration of unit being offline. The two costs are as shown, and are compared while determining the UC schedule and a best approach among them is chosen [95].

Start-up cost for Cold start:

$$STC = C_c(1-\varepsilon^{-t/\alpha})F + C_f \tag{III.1}$$

Start-up cost for Hot start:

$$STC = C_t tF + C_f \tag{III.2}$$

Where *STC* is the Start-up cost, C_c is the cold start cost in MBtu, F is the fuel cost, C_f is the fixed cost that includes crew expenses and maintenance expenses, C_t is cost in Mbtu/hour for maintaining the unit at operating temperature, αis the thermal time constant of the unit and *t* the time in hours the unit was allowed to cool.

The shut-down cost of a thermal unit is normally small compared with its start-up cost (Shutdown cost is generally taken as a constant value). A fixed shut-down cost, D_{ij}, may be used to reflect the labour cost and residual heat. lost involved in shutting down a unit [98].

III.4. Constraints :

The list of constraints is by no means exhaustive and depends on the individual utility's rules and reliability measures. Some of the constraints which reduce the freedom in the choice of starting up and shutting down of units in the system are listed below. These constraints can be brought in either because of unit technical issues or system operational requirements [98].

A thermal unit usually undergoes a gradual temperature changes, and this develops into a time period of some hours required to bring the unit on-line. When a unit is online its generation cannot be increased or decreased instantaneously owing to mechanical limitations.

And in general for turning *on* and turning *off* a unit in thermal systems requires a crew to operate. These all issues pose limitations in arriving at optimal UC schedule.

III.4.1. Minimum up/down Time :

In daily operation there is generally a requirement that a unit runs or stays shut-down for a certain minimum period of time before it changes status again. There may not be any technical reason why such restrictions should be imposed. However, frequent start-up and shut-down will cause the following problems to the station operation. They increase the thermal stress of the boiler and generator housing and hence reduce the expected operating life of a generating plant. They reduce the time period between scheduled maintenance outage and drain the limited resources on crew availability. Minimum on/off period is therefore generally specified by station managers [98].

Minimum up time :

Once a unit is committed and running, it should not be turned off immediately. It is an engineering consideration normally requires that a unit be running for at least a certain amount of time before it is shutdown [98]..

Minimum down time :

Once the unit is decmmitted, there is a minimum time gap before it can be committed and brought online again.

III.4.2. Crew constraints :

It is due to the limitation of personnel availability in the plant. If a plant consists of two or more units, both cannot be scheduled at the same time since there is no enough crew to attend both units while starting up or shutting down [91].

III.4.3. Must run units :

These units include pre-scheduled units which must be on-line. Some units are given a must-run status during certain times of the year for the reasons of voltage support on the transmission network i.e. a reliability and/or economic considerations [91].

III.4.4. Must out units :

Units which are on forced outages and maintenance are unavailable for commitment and are treated as must-out units [91].

III.4.5. Units on fixed generation :

These are the units which have been pre-scheduled and have their generation specified for certain time period. A unit on fixed generation is automatically a must run unit for the designated time period.

The system operator may pre-schedule certain units to must be “on”, must be “off” or fixed generation for certain intervals of the study period. Specification of such requirements are frequently issued by the system operators in the light of new data on the generation system. Scheduled out or forced out units can therefore be treated as must be “off” units. Units which are pre-specified on/off will reduce the commitment problem to certain extend. However, the output level of the must be “on” units affects the generation levels of the other synchronized units, the must be “on" units are necessarily included in the unit commitment decision process [98].

III.4.6. Fuel constraints :

These constraints applies in a system in which some units have limited fuel, or else have constraints that require them to burn a specified amount of fuel in a given time, presents a most challenging unit commitment problem.

III.4.7. Maximum and Minimum output limits of a unit :

These define the range in which the unit can actually be dispatched, these limits does not have any direct influence on the starting up and shutting down of the unit.

These output limits define the allowable output power of the generating units for the studying period. These limits are normally static, specified by the manufacturer. But as the generating unit ages, these limits may vary and must be verified by the power station manager from time to time. Outage of auxiliary equipment also temporarily affects the output power range of the plant. GT's outputs are sensitive to ambient temperature. The maximum output of GTs may need to be estimated in advance in associated with the forecast weather conditions [98]..

III.4.8. Ramp rate limits:

These represent the range of change in output over a unit time, used to prevent undesirable effects on generating units due to rapid changes in loading. When a unit is in the start-up stage, a pre-warming process must be introduced in order to prevent a brittle failure, especially when the unit start-up is a long process. Because of the unit physical limitations, the unit generating capability increases as a ramp function. Similarly, when a unit is in the shut-down process, it will take a while for the turbine to cool down. Before the unit generating capability decreases to its lower limit, the residual energy is to be used to meet the load demand. Therefore, because of the unit physical limitations, the unit generating capability increases as a ramp function [99–100].

III.4.9. Spinning Reserve:

Spinning reserve requirements are necessary in the operation of a power system in order to achieve minimum load interruptions. Spinning reserve is the term used to describe the total amount of generation available from all units synchronized (i.e., spinning) on the system, minus the present load and losses being supplied. Spinning reserve must be carried so that the loss of one or more units does not cause too far a drop in system frequency. Quite simply, if one unit is lost, there must be ample reserve on the other units to make up for the loss in a specified time period [95].

Spinning reserve requirements may be specified in terms of excess megawatt capacity or some form of reliability measures. Typical rules specify that reserve must be a given percentage of forecasted peak demand, or that reserve must be capable of making up the loss of the most heavily loaded unit in a given period of time. The amount of spinning reserve is an important factor in the assurance of uninterrupted supply to the customers and so is the distribution of spinning reserve among various generating plants based upon their responding time and relative distance to the load centers [95].

III.5. Unit Commitment Formulation :

Unit Commitment Problem is to decide which of the available units has to be turned on for the next period of time. The decision is subject to the minimization of fuel cost and to the various system and unit constraints. At the system level, the forecasted load demand should be satisfied by the units in service. In an interconnected system, the load demand should also include the interchange power required due to the contractual obligation between the different connected areas. Spinning reserve is the other system requirement to be satisfied while selecting the generating units. In addition, individual units are likely to have status restrictions during any given time period The problem becomes more complicated when minimum up time and down time requirements are considered, since they couple commitment decisions of successive hours [100-101].

The main objective of this optimization task is to minimize the total operating cost over the scheduled time horizon, while satisfying the different operational constraints. The operating cost includes start-up cost, shut down cost, running cost, maintenance cost etc. The UCP can be formulated as:

Minimize Operational cost

Subject to

- *Generation constraints,*
- *Reserve constraints,*
- *Unit capacity limits,*
- *Minimum Up time constraints,*
- *Minimum Down time constraints,*
- *Ramp rate constraints,*
- *Unit status restrictions,*

Objective function: Mathematically the objective function of unit commitment problem is the sum of fuel costs as well as start-up and shut-down cost of all generating units over a time frame, which needs to be minimized and can be represented as follows:

$$\min F = \underbrace{\left[\sum_{j=1}^{T}\sum_{i=1}^{N}(C_i(P_{ij}))\right]\times u_{ij}}_{\textbf{\textit{Production Cost}}} + \underbrace{\left[\sum_{j=1}^{T}\sum_{i=1}^{N}S_{ij}\right]\times u_{ij}(1-u_{ij-1}) + \left[\sum_{j=1}^{T}\sum_{i=1}^{N}D_{ij}\right]\times u_{ij-1}(1-{}^*u_{ij})}_{\textbf{\textit{Transition Cost}}}$$

(III.3)

where $C_i(P_{ij})$ fuel cost of unit i for generating power P_i at time j; S_{ij} start-up cost of unit i at time j; D_{ij} shut-down cost of unit i at time j, usually a fixed cost, U_{ij} ON('1')/OFF('0') status of unit i at time j,

The constraints

The variety of constraints to UCP can be broadly classified as System constraints and Unit constraints

System Constraints:

- *Load demand constraint*: The generated power from all the committed or on line units must satisfy the load balance equation

$$\sum_{i=1}^{N} P_{ik}U_{ik} = P_{Dk}; \qquad 1 \le k \le T \tag{III.4}$$

where $P_{D\,k}$ is the load demand at hour k.

- *Spinning reserve requirement*

$$\sum_{i=1}^{N}(P_i^{\max})\times u_{ij} \ge P_{Dj} + P_{Rj} \tag{III.5}$$

Where N number of units, T scheduling period in hours, P_{Dj} system load demand at time j, P_{Rj} system spinning reserve required at time j,

Unit Constraints:

- *Generation capacity constraints*: (*Unit Minimum and Maximum Output Limits)* Each generating unit is having the minimum and maximum capacity limit due to the different operational restriction on the associated boiler and other accessories

$$P_{\min(i)} \le P_{ik} \le P_{\max(i)}, \quad 0 \le i \le N-1, \quad 1 \le k \le T \tag{III.6}$$

- *Minimum up time/ down time constraint*: Minimum up time is the number of hours unit *i* must be ON before it can be turned OFF.
  Similarly, minimum down time restrict it to turn ON, when it is DOWN.

$$T_{ij}^{ON} > MUT_i \tag{III.7}$$

$$T_{ij}^{OFF} > MDT_i \tag{III.8}$$

- *Ramp rate limits:* The ramp rate limits restrict the amount of change of generation of a unit between two successive hours.

$$\begin{aligned} P_{ik} - P_{i(k-1)} &\le UR_i \\ P_{i(k-1)} - P_{ik} &\le DR_i \end{aligned} \tag{III.9}$$

  Where UR_i and DR_i are the ramp up and ramp down rates of unit *i* .
- *Unit status restrictions*: Some of the units will be given the status of 'Must Run' or 'Not available' due to the restrictions on the availability of fuel, maintenance schedule etc.

Where N number of units, T scheduling period in hours, P_{Dj} system load demand at time j, P_{Rj} system spinning reserve required at time j,

The start-up cost of a unit depends on the length of time the unit has been shut-down prior to starting up. Without loss of generality, the following start-up cost function is adopted:

$$S_{ij} = \begin{cases} HSC_i & T_i^{OFF} \le MDT_i + T_{cold\,i} \\ CSC_i & T_i^{OFF} > MDT_i + T_{cold\,i} \end{cases} \tag{III.10}$$

The start-up cost for a unit depends on its downtime. If it is longer than the related MDT_i plus its predefined Cold-Start hours ($T_{cold\,i}$), Cold-Start cost (CSC_i) is needed to operate it. Else if the i^{th} unit downtime is shorter than the mentioned duration, Hot-Start cost (HSC_i) is needed to operate it, where $T_{ij}^{ON/OFF}$ is the ON/OFF period of unit *i* at time *j*, and MUT_i/MDT_i is the minimum up/down time of unit *i*.

According to equation (III.3), when solving the UC problem, it is first necessary to determine the start-up, shut-down, and generation levels of all units over a specified period, which we can use the binary-coded evolutionary algorithm to search for feasible solutions. In addition, the scheduled units (combinations) must provide proper power for system demand, subject to power balance, spinning reserve requirement and individual unit constraints in the given interval. Thus, this is a non-linear problem that can be solved by advanced methods [101].

Figure III.2 depicts the various input data required by the unit commitment strategy, namely, the commitment schedule and the estimated production cost for the forecast load, the commitment schedule feeds the economic dispatch program for finer tuning of the load sharing between the committed units.

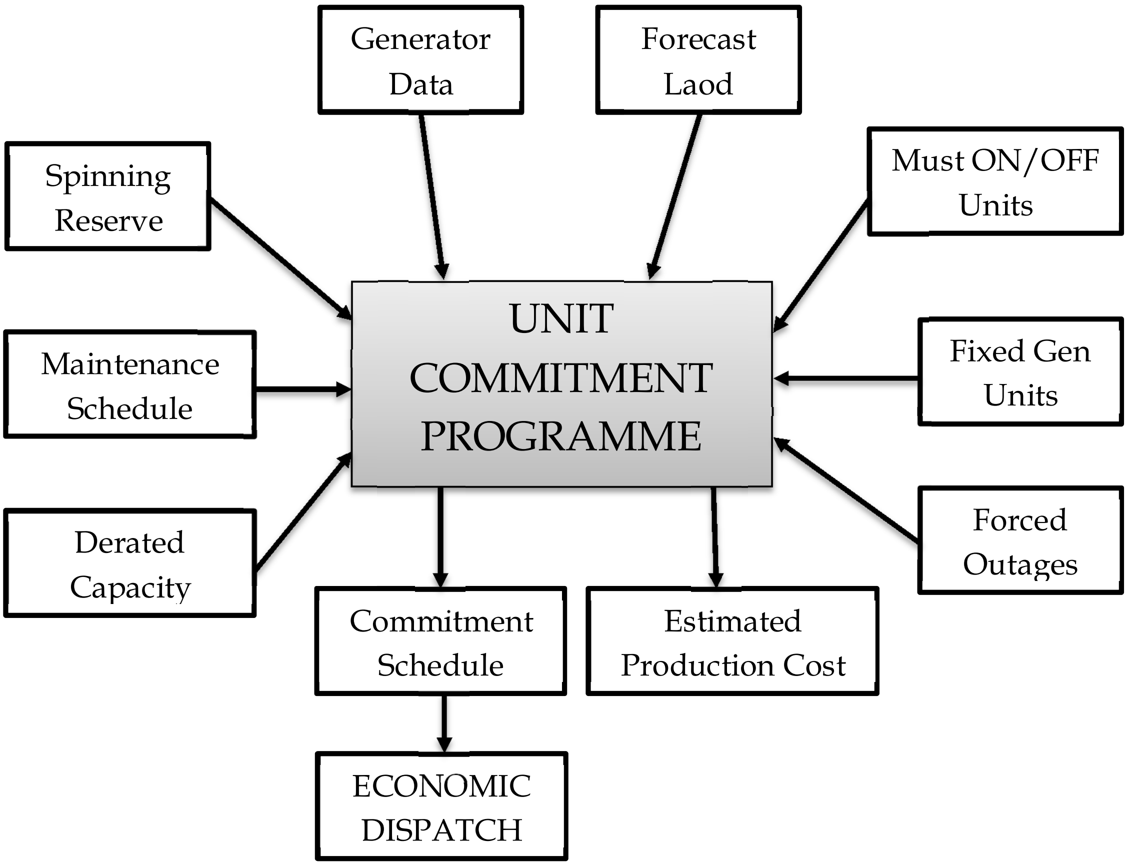


Figure III.2: *Input and Output data of Unit Commitment strategy*

III.6. Conclusion :

This chapter presented unit commitment as an operation scheduling function for management of generation resources for a short time horizon of one day or at most one week. Different unit commitment operational constraints were fully addressed and discussed. Different major procedure in problem formulation, search for a feasible solution through the minimization of the duality gap, updating the multimplier, and formalation of single-unit relaxed problems were shown.

CHAPTER IV

Solution methods: Evolutionary Computation and Metaheuristics algorithms

IV.1. Introduction :

Metaheuristic algorithms are often nature-inspired, and they are now among the most widely used algorithms for optimization [122–124]. They have many advantages over conventional algorithms, as we can see from many case studies presented in later chapters in this thesis.

In this chapter we present some general information about the metaheuristics that have been used to solve the economic dispatch and unit commitment problems. The metaheuristics covered include:

- Genetic Algorithm (GA),
- Particle Swarm Optimization (PSO),
- Pattern Search (PS),
- Big Bang–Big Crunch algorithm (BB–BC),
- Artificial Bee Colony algorithm (ABC),
- A hybrid GA–PS method,
- A hybrid PSO–PS method,
- A Hybrid BB–BC method.

In this chapter we provide general description of these metaheuristics, and we briefly revise the main features of the metaheuristic approaches, focusing particularly on those used in the following application chapters.

IV.2. Genetic Algorithm :

Genetic algorithm is a search method that employs processes found in natural biological evolution. These algorithms search or operate on a given population of potential solutions to find those that approach some specification or criteria. To do this, the genetic algorithm applies the principle of survival of the fittest to find better and better approximations. At each generation, a new set of approximations is created by the process of selecting individual potential solutions (individuals) according to their level of fitness in the problem domain and breeding them together using operators borrowed from natural genetics. This process leads to the evolution of population of individuals that are better suited to their environment than the individuals that they were created from, just as in natural adaptation [102].

IV.2.1. Overview of Genetic Algorithm :

Genetic algorithm (GAs) were invented by John Holland in the 1960s and were developed with his students and colleagues at the University of Michigan in the 70s. Holland's original goal was to investigate the mechanisms of adaptation in nature to develop methods in which these mechanisms could be imported into computer systems [103].

GA is a method for deriving from one population of "chromosomes" (e.g., strings of ones and zeroes, or bits) a new population. This is achieved by employing "natural selection" together with the genetics inspired operators of recombination (crossover), mutation, and inversion. Each chromosome consists of genes(e.g. bits), and each gene is an instance of a particular allele (e.g,0 or 1).The selection operator chooses those chromosomes in the population that will be allowed to reproduce, and on average those chromosomes that have a higher fitness factor(defined bellow),produce more offspring than the less fit ones. Crossover swaps subparts of two chromosomes, roughly imitating biological recombination between two single chromosome ("haploid") organisms; mutation randomly changes the allele values of some locations (locus) in the chromosome; and inversion reverses the order of a contiguous section of chromosome [103].

IV.2.2. Operators of Genetic Algorithm :

A basic genetic algorithm comprises three genetic operators.

- *Selection,*
- *Crossover,*
- *Mutation,*

Starting from an initial population of strings (representing possible solutions),the GA uses these operators to calculate successive generations. First, pairs of individuals of the current population are selected to mate with each other to form the offspring, which then form the next generation [104].

IV.2.2.1. ***Selection :***

This operator selects the chromosome in the population for reproduction. The more fit the chromosome, the higher its probability of being selected for reproduction. The various methods of selecting chromosomes for parents to crossover are [105],

- *Roulette-wheel selection,*
- *Boltzmann selection,*
- *Tournament selection,*
- *Rank selection,*
- *Steady-state selection,*

A. Roulette-wheel selection :

The commonly used reproduction operator is the proportionate reproductive operator where a string is selected from the mating pool with a probability proportional to P_i where F_i is the fitness value for that string. Since the population size is usually kept fixed in a simple GA, The sum of the probabilities of each string being selected for the mating pool must be one. The probability of the i^{th} selected string is [105]

$$P_i = \frac{F_i}{\sum_{j=1}^{n} F_j} \qquad \text{(IV.1)}$$

Where n is the population size.

B. Tournament selection :

GA uses a strategy to select the individuals from population and insert them into a mating pool. Individuals from the mating pool are used to generate new offspring, which are the basis for the next generation. As the individuals in the mating pool are the ones whose genes will be inherited by the next generation, it is desirable that the mating pool consists of good individuals .A selection strategy in GA is simply a process that the mating pool consists of good individuals .A selection strategy selection strategy in GA is simply a process that favors the selection of better individuals in the population for the mating pool [105].

IV.2.2.2. ***Crossover :***

The cross over operator involves the swapping of genetic material (bit-values) between the two parent strings. This operator randomly chooses a locus (a bit position along the two chromosomes) and exchanges the sub-sequences before and after that locus between two chromosomes to create two offspring. For example, the strings 1110 0001 0011 and 1000 0110 0111. The crossover operator roughly imitates biological recombination between two haploid (single chromosome) organisms. The crossover may be a single bit cross over or two bit cross over. In case of two bit crossover two points are chosen where the binary digits are swapped [105].

IV.2.2.3. ***Mutation :***

The two individuals (children) resulting from each crossover operation will now be subjected to the mutation operator in the final step to forming the new generation. This operator randomly flips or alters one or more bit values at randomly selected locations in a chromosome. For example, the string 1000 0001 0011 might be mutated in its second position to yield 1100 0001 0011. Mutation can occur at each bit position in a string with some probability and in accordance with its biological equivalent; usually this is very small, for example, 0.001. If 100% mutation occurs, then all of the bits in the chromosome have been inverted. The mutation operator enhances the ability of the GA to find a near optimal solution to a given problem by maintaining a sufficient level of genetic variety in the population, which is needed to make sure that the entire solution space is used in the search for the best solution. In a sense, it serves as an insurance policy; it helps prevent the loss of genetic material [105].

IV.2.2.4. ***Properties of GA :*** [103]

- Generally good at finding acceptable solutions to a problem reasonably quickly,
- Free of mathematical derivatives,
- No gradient information is required,
- Free of restrictions on the structure of the evaluation function,
- Fairly simple to develop,

- Do not require complex mathematics to execute,
- Able to vary not only the values, but also the structure of the solution,
- Get a good set of answers, as opposed to a single optimal answer,
- Make no assumptions about the problem space,
- Blind without the fitness function. The fitness function drives the population toward better,
- Solutions and is the most important part of the algorithm,
- Not guaranteed to find the global optimum solutions,
- Probability and randomness are essential parts of GA,
- Can by hybridized with conventional optimization methods,
- Potential for executing many potential solutions in parallel,
- Deals with large number of variables,
- Provides a list of optimum variables.

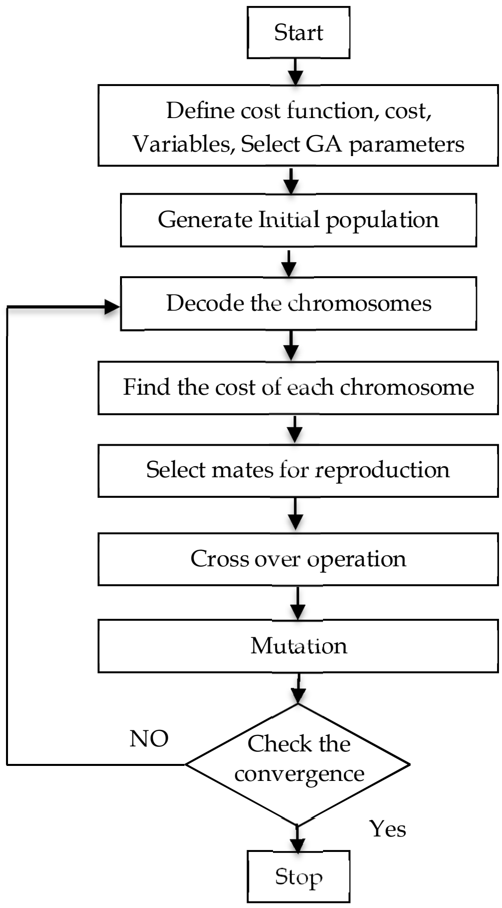


Figure IV.1 : *Flow chart of GA Algorithm.*

In this part various operators of genetic algorithm like selection, crossover and mutation are discussed. Advantages and disadvantages of the Genetic Algorithm over the other optimization technique are also discussed. The Flow chart of GA is also discussed.

IV.3. Particle Swarm Optimization :

Particle swarm optimization (PSO) is a population based stochastic optimization technique developed by Dr. Ebehart and Dr. Kennedy in 1995 [106], inspired by social behavior of bird flocking or fish schooling. PSO shares many similarities with evolutionary computation techniques such as Genetic Algorithms (GA). The system is initialized with a population of random solutions and searches for optima by updating generations. However, unlike GA, PSO has no evolution operators such as crossover and mutation. In PSO, the potential solutions, called particles, fly through the problem space by following the current optimum particles. The detailed information will be given in following sections. Compared to GA, the advantages of PSO are that PSO is easy to implement and there are few parameters to adjust. PSO has been successfully applied in many areas: function optimization, artificial neural network training, fuzzy system control, and other areas where GA can be applied [105].

IV.3.1. Back ground of Artificial Intelligence :

The term "Artificial Intelligence" (AI) is used to describe research into human-made systems that possess some of the essential properties of life. AI includes two-folded research topic [64].

- AI studies how computational techniques can help when studying biological phenomena,
- AI studies how biological techniques can help out with computational problems,

The focus of this report is on the second topic. Actually, there are already lots of computational techniques inspired by biological systems. For example, artificial neural network is a simplified model of human brain; genetic algorithm is inspired by the human evolution. Here we discuss some types of biological system-social system, more specifically, the collective behaviors of simple individuals interacting with their environment and each other. Someone called it as swarm intelligence. All of the simulations utilized local processes, such as those modeled by cellular automata, and might underlie the unpredictable group dynamics of social behavior. Some popular examples are bees and birds. Both of the simulations were created to interpret the movement of organisms in a bird flock or fish school. These simulations are normally used in computer animation or computer aided design. There are two popular swarm inspired methods in computational intelligence areas: Ant colony optimization (ACO) and particle swarm optimization (PSO). ACO was inspired by the behaviors of ants and has many successful applications in discrete optimization problems. The particle swarm concept originated as a simulation of simplified social system. The original intent was to graphically simulate the choreography of bird of a bird block or fish school. However, it was found that particle swarm model could be used as an optimizer [64].

IV.3.2. Particle Swarm Optimization :

PSO simulates the behaviors of bird flocking. Suppose the following scenario: a group of birds are randomly searching food in an area. There is only one piece of food in the area being searched. All the birds do not know where the food is. But they know how far the food is in each iteration. So what's the best strategy to find the food? The effective one is to follow the bird, which is nearest to the food. PSO learned from the scenario and used it to solve the optimization problems. In PSO, each single solution is a "bird" in the search space. We call it "particle". All of particles have fitness values, which are evaluated by the fitness function to be optimized, and have velocities, which direct the flying of the particles. The particles fly through the problem space by following the current optimum particles. PSO is initialized with a group of random particles (solutions) and then searches for optima by updating generations. In every iteration, each particle is updated by following two "best" values [4].

The first one is the best solution (fitness) it has achieved so far. (The fitness value is also stored). This value is called p_{best}. Another "best" value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the population. This best value is a global best and called g_{-best}. When a particle takes part of the population as its topological neighbors, the best value is a local best and is called p_{-best}. After finding the two best values, the particle updates its velocity and positions with following equation (IV.1) and (IV.2).

$$V_i^{(u+1)} = w * V_i^{(u)} + C_1 * rand() * (pbest_i - P_i^{(u)}) + C_2 * rand() * (gbest_i - P_i^{(u)}) \quad \text{(IV.2)}$$

$$P_i^{(u+1)} = P_i^{(u)} + V_i^{(u+1)} \quad \text{(IV.3)}$$

In the above equation [4],

The term $rand(\,)*(p_{best\,i}\text{-}P_i(u))$ is called particle memory influence

The term $rand(\,)*(\,g_{best\,i}\,\text{-}P_i(u))$ is called swarm influence.

$V_i^{\,(u)}$ which is the velocity of i^{th} particle at iteration 'u' must lie in the range

$$V_{\min} \le V_i^{(u)} \le V_{\max} \quad \text{(IV.4)}$$

- The parameter V_{max} determines the resolution, or fitness, with which regions are to be searched between the present position and the target position.
- If V_{max} is too high, particles may fly past good solutions. If V_{min} is too small, particles may not explore sufficiently beyond local solutions.
- In many experiences with PSO, V_{max} was often set at 10-20% of the dynamic range on each dimension.
- The constants C_1 and C_2 pull each particle towards p_{best} and g_{best} positions.
- Low values allow particles to roam far from the target regions before being tugged back. On the other hand, high values result in abrupt movement towards, or past, target regions.
- The acceleration constants C_1 and C_2 are often set to be 2.0 according to past experiences.
- Suitable selection of inertia weight 'ω' provides a balance between global and local explorations, thus requiring less iteration on average to find a sufficiently optimal solution.
- In general, the inertia weight w is set according to the following equation,

$$w = w_{\max} - \left[\frac{w_{\max} - w_{\min}}{ITER_{\max}}\right] \times ITER \quad \text{(IV.5)}$$

Where w is the inertia weighting factor,

w_{max} - maximum value of weighting factor,

w_{min} - minimum value of weighting factor,

$Iter_{max}$ - maximum number of iterations, *Iter* - current number of iteration.

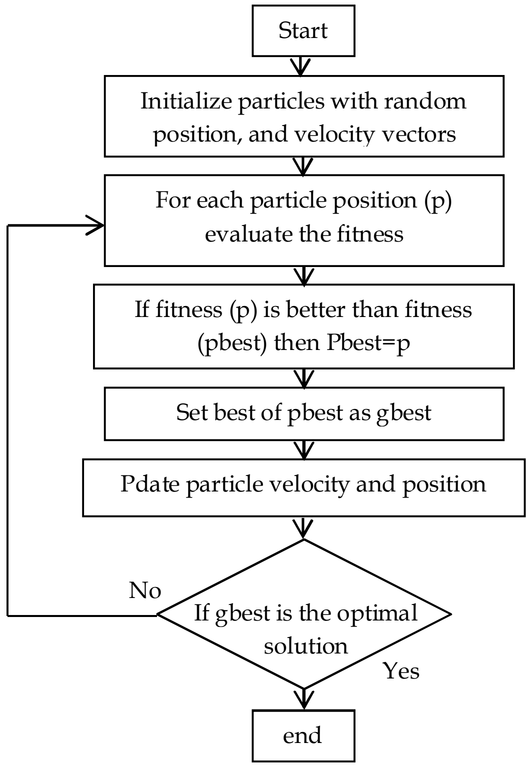


Figure IV.2 : *Flow chart of PSO Algorithm.*

The detail of particle swarm optimization technique is discussed in this section. Various parameters of PSO and their effects are also discussed. Algorithm of PSO optimization technique and the flow chart is discussed briefly.

IV.4. Pattern Search method (PS) :

A particular family of global optimization methods, known as Direct Search methods, originally introduced and developed by researchers in 1960s, has recently received some attention. The Direct Search methods are simply structured to explore a set of points, in the vicinity of the current position, looking for a smaller objective function value than the current one. This family includes Pattern Search (PS) algorithms, Simplex Methods (SM), Powell Optimization (PO) and others. Direct Search methods, in contrast to more standard optimization methods, are often called derivative-free as they do not require any information about the gradient (or higher derivative) of the objective function when searching for an optimal solution. Therefore Direct Search methods are particularly appropriate for solving non-continuous, non-differentiable and multimodal (i.e. multiple local optima) optimization problems [107].

The Pattern Search (PS) optimization routine is an evolutionary technique that is suitable to solve a variety of optimization problems that lie outside the scope of the standard optimization methods. Generally, PS has the advantage of being very simple in concept, and easy to implement and computationally efficient algorithm. Unlike other heuristic algorithms, such as GA, PS possesses a flexible and well-balanced operator to enhance and adapt the global and fine tune local search. A historic discussion of direct search methods for unconstrained optimization is presented in reference [107].

The Pattern Search (PS), algorithm proceeds by computing a sequence of points that may or may not approaches to the optimal point. The algorithm starts by establishing a set of points called mesh, around the given point. This current point could be the initial starting point supplied by the user or it could be computed from the previous step of the algorithm.

The mesh is formed by adding the current point to a scalar multiple of a set of vectors called a pattern. If a point in the mesh is found to improve the objective function at the current point, the new point becomes the current point at the next iteration.

The Pattern search begins at the initial point X_0 that is given as a starting point by the user. At the first iteration, with a scalar=1 called mesh size, the pattern vectors are constructed as [0 1], [1 0], [-1 0] and [0 -1], they may be called direction vectors. Then the Pattern search algorithm adds the direction vectors to the initial point X_0 to compute the following mesh points:

$$X_0+[0 \quad 1], \quad X_0+[1 \quad 0], \quad X_0+[-1 \quad 0] \quad and \quad X_0+[0 \quad -1] \tag{IV.6}$$

Fig. IV.3 illustrates the formation of the mesh and pattern vectors. The algorithm computes the objective function at the mesh points in the order shown. The algorithm polls the mesh points by computing their objective function values until it finds one whose value is smaller than the objective function value of X_0. If there is such point, then the poll is successful and the algorithm sets this point equal to X_1 [108].

After a successful poll, the algorithm steps to iteration 2 and multiplies the current mesh size by 2. The mesh at iteration 2 contains the following points:

$$X_1 + 2\times[0 \quad 1], \quad X_1 + 2\times[1 \quad 0], \quad X_1 + 2\times[-1 \quad 0] \quad and \quad X_1 + 2\times[0 \quad -1]$$

The algorithm polls the mesh points until it finds one whose value is smaller the objective function value of X_1. The first such point it finds is called X_2, and the poll is successful. Because the poll is successful, the algorithm multiplies the current mesh size by 2 to get a mesh size of 4 at the third iteration because the expansion factor =2.

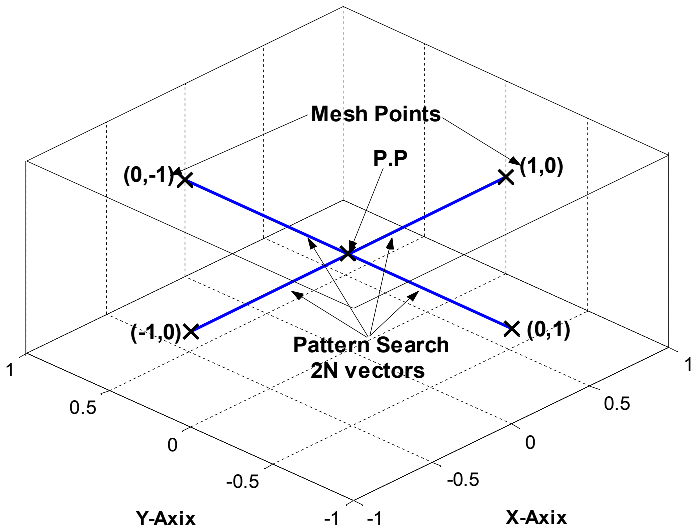


Figure IV.3 : *2N Pattern Vectors which forms the mesh points.*

Now if iteration 3, (mesh size = 4), ends up being unsuccessful poll, i.e. none of the mesh points has a smaller objective function value than the value at X_2, so the poll is called an unsuccessful poll. In this case, the algorithm does not change the current point at the next iteration. That is, $X_3 = X_2$. At the next iteration, the algorithm multiplies the current mesh size by 0.5, a contraction factor, so that the mesh size at the next iteration is smaller. The algorithm then polls with a smaller mesh size [108].

The PS method generates a sequence of iterates $\{x^{(1)}, x^{(2)}, \ldots x^{(k)}, \ldots\}$ with non-increasing objective function values. In each iteration k, there are two important steps of the PS method namely, the SEARCH step and the POLL step. Note that we use the value $r = 2n$ in the description of the PS method [109].

In the SEARCH step, the objective function is evaluated at a finite number of points (say a maximum of V points) on a mesh (a discrete subset of $\Re^n$) so as to improve the current iterate. The mesh at the current iterate, $x^{(k)}$, is given by

$$M_k = \left\{ m \in \Re^n \middle| m = x^{(k)} + \Delta_k D_q : q \in Z_+^r \right\}, \tag{IV.7}$$

Where m is a mesh trial point, $\Delta_k > 0$ is a mesh size parameter (also known as the step size control parameter) which depends on the iteration k, and Z_+ is the set of nonnegative integers. There are no specific rules on how to generate trial points of the SEARCH step in the current mesh. Users may generate these points by some heuristic rules. The aim of the SEARCH step is to find a feasible trial point (on a mesh M_k) that yields a lower objective function value than the function value at $x^{(k)}$. A SEARCH step is therefore successful if there exists a feasible trial point $m \in M_k$ (where m is one of the V points) such that $f(m) < f(x^{(k)})$. In such a case, m is treated as the new iterate and the step size Δ_k is increased so as to choose the next trial points on a magnified mesh than the previous mesh. If the SEARCH step is unsuccessful in improving the current iterate $x^{(k)}$, a second step, called the POLL step, is executed around $x^{(k)}$ with the aim of decreasing the objective function value. This step must be done before terminating the iteration [109].

The POLL step generates trial points at the poll set around the current iterate, $x^{(k)}$, as shown in fig. IV.3, for the case of a two dimensional problem, where $\Delta_k = 1$. The poll set is composed of trial points that are positioned a step Δ_k away from the current iterate $x^{(k)}$, along the direction designated by the columns of D. This poll set is denoted by P_k and is defined by

$$P_k = \left\{ p_i \in \Re^n \middle| p_i = x^{(k)} + \Delta_k d_i : d_i \in D, i := 1,\ldots,r \right\}, \tag{IV.8}$$

Where p_i is a trial point in the POLL step. The order in which the points in P_k are evaluated can also differ and has no effect on convergence. We now present the step by step description of the PS algorithm [110] using both the SEARCH and the POLL step.

In most implementation of the PS method, the initial step size parameter $\Delta_0 = 1$ is used and the updating of the step size parameter is carried out by

$$\Delta_{k+1} = \begin{cases} 2\Delta_k \text{ if } f(p_i) < f(x^{(k)}), \text{for some } p_i \in P_k,\ \theta_k = 2, \\ \dfrac{1}{2}\Delta_k \text{ otherwise}, \varphi_k = \dfrac{1}{2} \end{cases} \tag{IV.9}$$

IV.5. Big Bang-Big Crunch method :

The Big Bang–Big Crunch (BB-BC) optimization method it is relies on one of the theories of the evolution of the universe namely, the Big Bang and Big Crunch theory is introduced by Erol and Eksin which has a low computational time and high convergence speed. According to this theory, in the Big Bang phase energy dissipation produces disorder and randomness is the main feature of this phase; whereas, in the Big Crunch phase, randomly distributed particles are drawn into an order. The Big Bang-Big Crunch (BB-BC) Optimization method similarly generates random points in the Big Bang phase and shrinks these points to a single representative point via a center of mass in the Big Crunch phase. After a number of sequential Big Bangs and Big Crunches where the distribution of randomness within the search space during the Big Bang becomes smaller and smaller about the average point computed during the Big Crunch, the algorithm converges to a solution. The BB-BC method has been shown to outperform the enhanced classical Genetic Algorithm for many benchmark test functions [111].

IV.5.1. Big Bang–Big Crunch (BB–BC) Optimization Algorithm :

The BB–BC method developed by Erol and Eksin consists of two phases: a Big Bang phase, and a Big Crunch phase. In the Big Bang phase, candidate solutions are randomly distributed over the search space. Similar to other evolutionary algorithms, initial solutions are spread all over the search space in a uniform manner in the first Big Bang. Erol and Eksin [111] associated the random nature of the Big Bang to energy dissipation or the transformation from an ordered state (a convergent solution) to a disorder or chaos state (new set of solution candidates).

Randomness can be seen as equivalent to the energy dissipation in nature while convergence to a local or global optimum point can be viewed as gravitational attraction. Since energy dissipation creates disorder from ordered particles, we will use randomness as a transformation from a converged solution (order) to the birth of totally new solution candidates (disorder or chaos) [111].

The proposed method is similar to the GA in respect to creating an initial population randomly. The creation of the initial population randomly is called the Big Bang phase. In this phase, the candidate solutions are spread all over the search space in an uniform manner [111].

The Big Bang phase is followed by the Big Crunch phase. The Big Crunch is a convergence operator that has many inputs but only one output, which is named as the ‘‘center of mass”, since the only output has been derived by calculating the center of mass. Here, the term mass refers to the inverse of the merit function value [112]. The point representing the center of mass that is denoted by x_c is calculated according to:

$$\vec{x}^c = \frac{\sum_{i=1}^{N} \frac{1}{f^i} \vec{x}^i}{\sum_{i=1}^{N} \frac{1}{f^i}} \tag{IV.10}$$

where x_i is a point within an n-dimensional search space generated, f_i is a fitness function value of this point, N is the population size in Big Bang phase. The convergence operator in the Big Crunch phase is different from ‘exaggerated’ selection since the output term may contain additional information (new candidate or member having different parameters than others) than the participating ones, hence differing from the population members. This one step convergence is superior compared to selecting two members and finding their center of gravity. This method takes the population members as a whole in the Big-Crunch phase that acts as a squeezing or contraction operator; and it, therefore, eliminates the necessity for two-by-two combination calculations [111].

After the second explosion, the center of mass is recalculated. These successive explosion and contraction steps are carried repeatedly until a stopping criterion has been met. The parameters to be supplied to normal random point generator are the center of mass of the previous step and the standard deviation. The deviation term can be fixed, but decreasing its value along with the elapsed iterations produces better results.

After the Big Crunch phase, the algorithm creates the new solutions to be used as the Big Bang of the next iteration step, by using the previous knowledge (center of mass). This can be accomplished by spreading new off-springs around the center of mass using a normal distribution operation in every direction, where the standard deviation of this normal distribution function decreases as the number of iterations of the algorithm increases [112]:

$$x^{new} = x^c + l.r / k \tag{IV.11}$$

where x^c stands for center of mass, l is the upper limit of the parameter, r is a normal random number and k is the iteration step. Then new point x^{new} is upper and lower bounded.

The BB–BC approach takes the following steps [111]:

Step.1 Form an initial generation of N candidates in a random manner. Respect the limits of the search space.

Step.2 Calculate the fitness function values of all the candidate solutions.

Step.3 Find the center of mass according to (IV.10). Best fitness individual can be chosen as the center of mass.

Step.4 Calculate new candidates around the center of mass by adding or subtracting a normal random number whose value decreases as the iterations elapse of using (IV.11).

Step.5 Return to Step 2 until stopping criteria has been met.

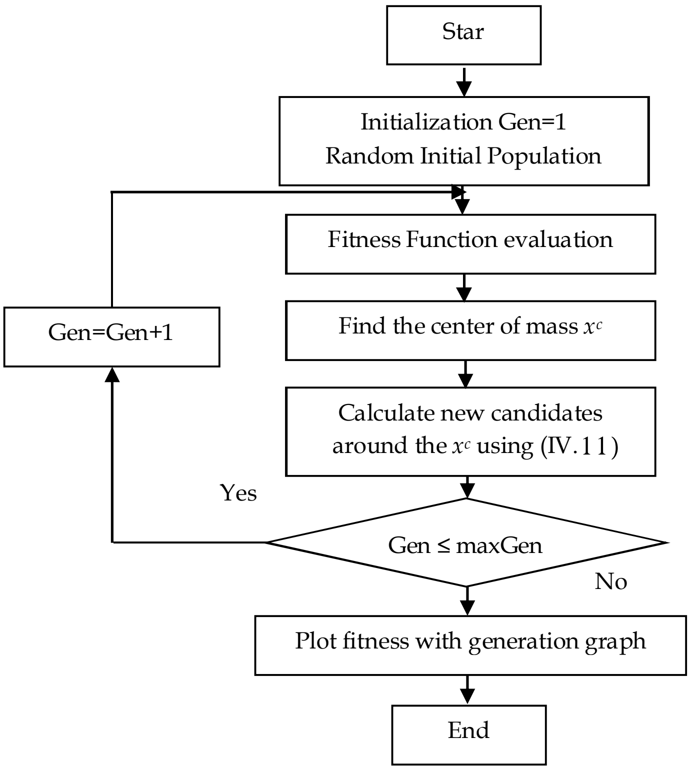


Figure IV.4: *BB–BC computational procedure.*

IV.6. Artificial Bee Colony optimization :

Artificial bee colony (ABC) optimization algorithms are formulated based on the natural foraging behavior of honey bees. ABC was first developed by Dr. Korba. [113–114] Some artificial ideas are added to construct a robust ABC. Unlike classical search and optimization methods, ABC starts its search with a random set of solutions (colony size), instead of a single solution just like GA. Each population member is then evaluated for the given objective function and is assigned fitness. The best fits are entertained for the next generation while the others are discarded and compensated by a new set of random solutions in each generation. The only stopping criterion is the completion of maximum no of cycles or generations. At the end of the cycles, the solution of the best fit is the desired solution.

IV.6.1. ABC foraging behavior :

To find the optimal decision variables, to optimize an objective function and to satisfy the constraints, the variables are bounded to the limits. Eq. (6) gives a function defined to take care of variable bounds [113].

VI.6.1.1. *Random solution generation :*

Food sources which are in their proximity are selected by the employed bees when they move to a new location. Each employed bee associated with a food source is responsible for nectar extraction from it [113].

$$P_i = P_{i\min} + \text{rand}\,(0, 1) \times (P_{i\max} - P_{i\min}), \tag{IV.12}$$

$\forall\, i \in \{1,2,3, \ldots, n_g\}$,

where $P_{i\min}$ and $P_{i\max}$ are the lower and upper bounds of variable P_i. In Eq. (IV.12) rand (0, 1) represents a random number between 0 and 1.

The solution is represented in a matrix form as

$$\boldsymbol{X}_i = \left[P_1\ P_2\ \ P_3\ \ P_4\ \ P_5 \ldots P_{n_g} \right]. \tag{IV.13}$$

Similarly the food sources $\{\boldsymbol{X}_1,\ \boldsymbol{X}_2,\ \boldsymbol{X}_3,\ \boldsymbol{X}_4, \ldots,\ \boldsymbol{X}_n\}$ is the set of all the randomly chosen solutions which satisfies all the defined constraints.

IV.6.1.2. *Evaluation of fitness of solutions :*

The food sources are ranked based on the quality and quantity of their nectar. Similarly, fitness is assigned to each solution, which represents the goodness of each solution [113].

$$\text{Fitness }(i) = \frac{1}{1+\sum F_i} \quad \forall\, i \in \{1, 2, 3, \ldots, n_g\}, \tag{IV.14}$$

where $\sum F_i$ represents the total fuel cost of generation.

IV.6.1.3. *Employed bee phase :*

Each solution is handled by an employed bee who searches for the food source in their neighborhood and if a better food source is found it discards its previous food source and starts exploring the new one until it finds a better food source [113].

Similarly, a mutant solution is generated for each solution using its randomly selected neighbor and the parameter to be changed. $\{\boldsymbol{X}_1, \boldsymbol{X}_2, \boldsymbol{X}_3, \boldsymbol{X}_4, \ldots, \boldsymbol{X}_n\}$ is the solution set where each solution $\boldsymbol{X}_i$ is represented as

$$\boldsymbol{X}_i = \left[P_1\, P_2\;\, P_3\;\, P_4\;\, P_5 \ldots P_{n_g}\right].$$

A random variable of all n_g variables is chosen and a neighbor of all n–1 neighbors is chosen randomly and a mutant solution is produced as

$$\boldsymbol{X}_{1\text{mutant}} = \boldsymbol{X}_1\,(i) + (\boldsymbol{X}_j\,(i) - \boldsymbol{X}_1(i)) \times \left(2 \times \text{rand} - 1\right), \tag{IV.15}$$

where i and j is the randomly chosen parameter and the neighbor, respectively.

A greedy selection between the mutant and original solutions takes place resulting in the discard of the least fit solution. This process of selection is repeated for each solution. The solution whose mutant is less fit increases its trial and may lead to dissertation of the food source if the trial leads to a threshold limit [113].

IV.6.1.4. *Onlooker bee phase :*

The onlooker bees in the hive detect a food source by means of the information presented to them by the employed foragers. A food source is chosen with the probability which is proportional to its food quality. Different schemes can be used to calculate the probability values [114]. For example

$$\text{Probability } (i) = \frac{\text{Fitness } (i)}{\text{sum (Fitness)}},$$
$$\text{Probability } (i) = \frac{a \times \text{Fitness}(i)}{\max(\text{Fitness}) + b}. \tag{IV.16}$$

where $a + b = 1$.

A random number chosen which represents the expectancy of the onlooker bee is compared with the probability of a solution (food). If the solution meets the expectancy of the onlooker, then it moves to exploit the food source and becomes an employed bee and corresponding employed bee of food source retires [114].

The new employed bee starts exploring the neighborhood and repeats the employed bee behavior.

If the expectancy is not reached, the onlooker chooses other food source (solution) with different expectancy until it becomes employed. The above procedure repeats while all the onlooker bees get employed to food source. The food source with the highest probability will be chosen maximum and the one with least probability is discarded more times [113].

IV.6.1.5. *Scout bee phase :*

The scout bee is to explore the search area and it is often represented by a randomly generated solution. It will replace an employed bee if its trials of mutation exceed a threshold limit [113].

The scout will encourage the exploration of unexplored area of the search space. The best solution and fitness values are memorized for every iteration. The above process is repeated for maximum number of iterations and the result at the end will ensure a global minimum or maximum [114].

IV.6.2. ABC algorithm :

The proposed ABC algorithm is summarized as follows [113]:

Step 1. Read the line input data; Initialize MaxIterC (maximum iteration count) and base case as the best solution;

Step 2. Construct initial bee population (solution) X_{ij} as each bee is formed by the open switches in the configuration and the number of employed bees are equal to onlooker bees;

Step 3. Evaluate the fitness value for each employed bee by using Eq. (IV.14);

Step 4. Initialize cycle=1;

Step 5. Generate a new population (solution) V_{ij} in the neighborhood of X_{ij} for employed bees using Eq. (IV.15) and evaluate them;

Step 6. Apply the greedy selection process between X_i and V_i;

Step 7. Calculate the probability values P_i for the solutions X_i by means of their fitness values using Eq (IV.16);

Step 8. Produce the new populations V_i for the onlookers from the populations X_i, selected depending on P_i by applying roulette wheel selection process, and evaluate them;

Step 9. Apply the greedy selection process for the onlookers between X_i and V_i;

Step 10. Determine the abandoned solution, if exists, and replace it with a new randomly produced solution X_i for the scout bees using Eq. (IV.12);

Step 11. Memorize the best solution achieved so far;

Step 12. Cycle=cycle+1;

Step 13. If cycle<MIC, go to Step 5, otherwise go to Step 14;

Step 14. Stop.

IV.7. A hybrid GA–PS method :

This section presents a new approach based on a hybrid algorithm consisting of Genetic Algorithm (GA) and Pattern Search (PS). GA is the main optimizer of the algorithm, whereas PS are used to fine tune the results of GA to increase confidence in the solution.

The main objective of this study is to introduce a hybrid method that combines the Genetic Algorithm (GA) and Pattern Search (PS)–referred to as the hybrid GA–PS method– in the context of power system problem.

All the parameters involved in the Pattern search optimization algorithm can be pre-defined subject to the nature of the problem being solved.

The above steps and how PS evolves are depicted by the flow chart of fig. IV.5. It should be noted that all the parameters involved in the pattern search optimization algorithm can be pre-defined subject to the nature of the problem being solved.

This part describes a novel hybrid approach based on a combination of Genetic Algorithm (GA) and Pattern Search (PS) to study power system problems. The GA–PS technique has overcome an important drawback of the PS methods that is the need to supply a suitable starting point. This shortcoming of the PS methods was highlighted in the previous work of the authors as it makes any optimization method relying on a good choice of the initial point possibly more susceptible to getting trapped in local minima, although the much improved speed of computation allows for additional searches to be made to increase the confidence in the solution. The hybrid GA–PS algorithm, on the other hand, does not require the user to specify the starting point as it is generated automatically for the PS stage by the initial GA phase. Moreover, the performance of the proposed hybrid method improves with the increase of size and complexity of the system. Overall, the proposed algorithm has been shown to perform extremely well for solving economic dispatch problems.

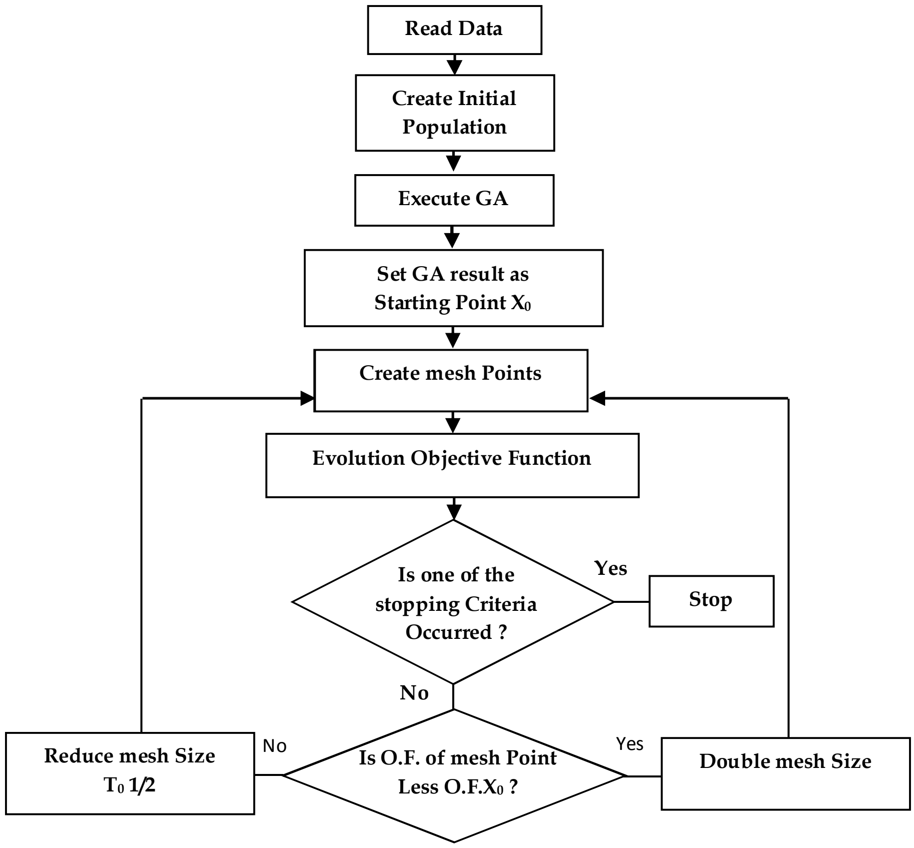


Figure IV.5 : *Flow chart of GA–PS Algorithm.*

IV.8. A hybrid PSO-PS method :

In the proposed PSO-PS, pattern search is employed to conduct exploitation of the parameters solution space. The hybrid algorithm implemented is inspired in the strategy suggested in [115–116] of exploring the search space first globally and then locally, using two different evolutionary algorithms.

In this work, due to the fact that in high dimension problems the PSO is easily trapped into local optima, resulting in a low optimizing precision or even failure [117], the proposal is to use the PSO algorithm to provide a good initial solution as a starting point for a pattern search algorithm PS.

In this section, the hybridization of PS method and PSO are incorporated in the optimization process in order to look for the global optimal solution for the fitness function and decision variables as well as minimum computational CPU time.

Fig. IV.6 depicts the schematic representation of the proposed HPSO-PS algorithm.

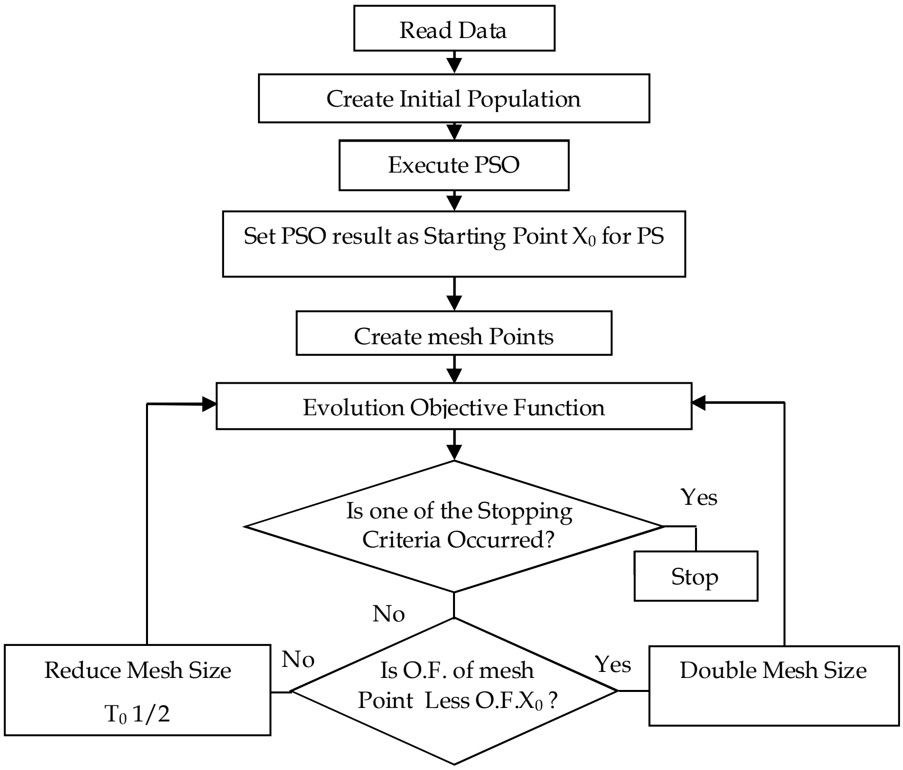


Figure IV.6: *Flow chart of HPSO-PS method.*

IV.9. A Hybrid Big Bang–Big Crunch Optimization Algorithm :

In this section, a new optimization method relied on one of the theories of the evolution of the universe namely, the Big Bang and Big Crunch theory is introduced by Erol and Eksin [118] which has a low computational time and high convergence speed. According to this theory, in the Big Bang phase energy dissipation produces disorder and randomness is the main feature of this phase; whereas, in the Big Crunch phase, randomly distributed particles are drawn into an order. The Big Bang–Big Crunch (BB–BC) Optimization method similarly generates random points in the Big Bang phase and shrinks these points to a single representative point via a center of mass in the Big Crunch phase. After a number of sequential Big Bangs and Big Crunches where the distribution of randomness within the search space during the Big Bang becomes smaller and smaller about the average point computed during the Big Crunch, the algorithm converges to a solution. The BB–BC method has been shown to outperform the enhanced classical Genetic Algorithm for many benchmark test functions [112].

The HBB–BC method consists of two phases: a Big Bang phase where candidate solutions are randomly distributed over the search space, and a Big Crunch phase working as a convergence operator where the center of mass is generated. Then new solutions are created by using the center of mass to be used as the next Big Bang [112]. These successive phases are carried repeatedly until a stopping criterion has been met. This algorithm not only considers the center of mass as the average point in the beginning of each Big Bang, but also similar to Particle Swarm Optimization-based approaches [6], utilizes the best position of each particle and the best visited position of all particles. As a result because of increasing the exploration of the algorithm, the performance of the BB–BC approach is improved [112].

A hybrid BB–BC algorithm :

The BB–BC method in the process of selection of a new generation depends on centre of mass only, where we find kind of randomized in this the choice.

Although BB–BC performs well in the exploitation (the fine search around a local optimum), there are some problems in the exploration (global investigation of the search place) stage. If all of the candidates in the initial Big Bang are collected in a small part of search space, the BB–BC method may not find the optimum solution and with a high probability, it may be trapped in that sub domain [112].

One can consider a large number for candidates to avoid this defect, but it causes an increase in the function evaluations as well as the computational costs. This paper uses the Particle Swarm Optimization (PSO) [3] capacities to improve the exploration ability of the BB–BC algorithm [119].

In order to improve the computational efficiency of BB-BC algorithm, Kaveh and Talatahari [119] uses the social behavior of bird flocking and fish schooling model in particle swarm optimization. The swarm's movement is directed by both their own experience and the population's experience. For every iteration, a particle moves towards a direction computed from the local best solution and the global best solution. This concept is used in this research work where the BB-BC algorithm not only utilizes the center of mass but also employs the global best solution to generate the new solution.

A modified version of eq.(II.10) is given as

$$X^{new} = \alpha_1.X^c + (1-\alpha_1).(\alpha_2.X^{lbest} + (1-\alpha_2).X^{gbest}) + \alpha_3.l.r/k \qquad (IV.17)$$

where X_{lbest} is the best position of the particle up to the iteration *k* and X_{gbest} is the best position among all candidates up to the iteration *k*; α_1, α_2 and α_3 are adjustable parameters controlling the influence of the global best and local best on the new position of the candidates.

The hybrid BB–BC approach similarly not only uses the center of mass but also utilizes the best position of each candidate (P_{best}) and the best global position (G_{best}) to generate a new solution.

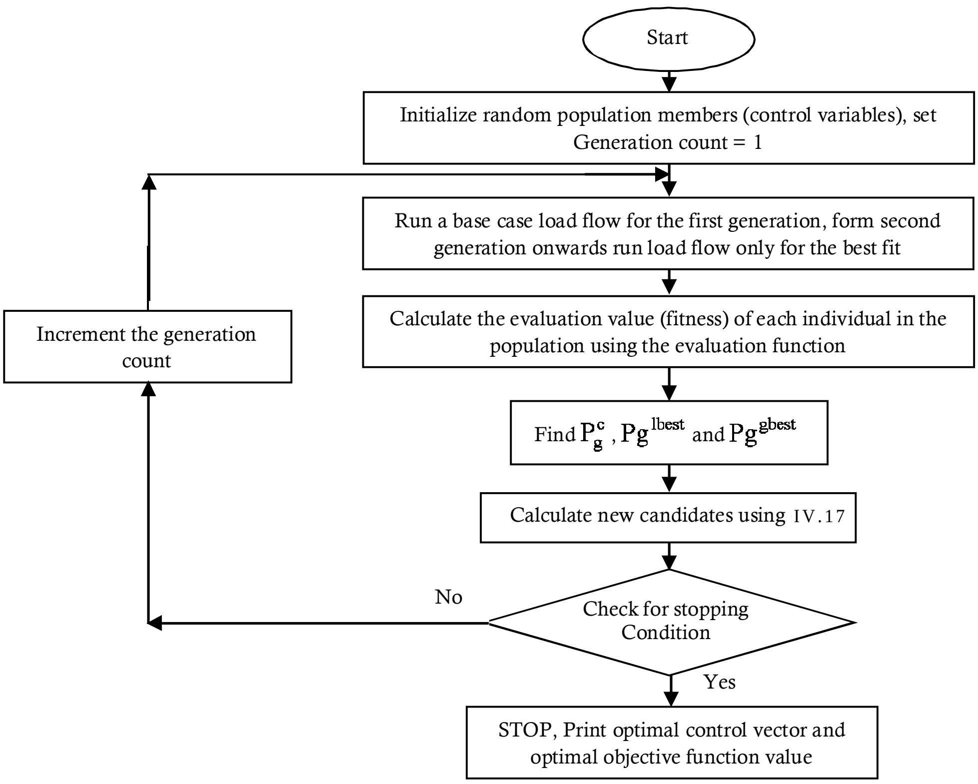


Figure IV.7: *Flowchart of the proposed HBB–BC algorithm.*

Fig. IV.7 depiction of the schematic representation of the proposed algorithm to solve the ED problem.

IV.10. Conclusion:

In this chapter we presented overview and exposes the common and basic concepts for various metaheuristics techniques based on GA, PSO, PS, BB-BC and ABC and we briefly discussed the mechanisms and characteristics of these techniques. Next chapter presents a detailed design of these approaches and their implementation with ED and UC problems will be provided.

CHAPTER V

Application of Artificial Intelligence techniques to Economic Load Dispatch problems

V.1. Introduction :

This chapter presents the performance of various metaheuristic techniques based on GA, PSO, PS, BB-BC and ABC for solving various types of ED problem for estimation of the finest combination of generated power in a given system at lowest operating cost while sustaining the operating condition of system efficiently. The fuel cost is minimized by satisfying the nonlinear operating conditions of thermal units mainly based on generation capacity constraints, generator ramp limit, power balance constraints, and valve point loading effect and by keeping in view the prohibited operating zones, respectively. About the optimization, a comparative study is made for the various metaheuristic approaches and their hybrid versions such as GA-PS, PSO-PS and HBB-BC.

Knowledge-based or Artificial Intelligence techniques are used increasingly as alternatives to more classical techniques to model environmental systems. Artificial Intelligence (AI) could be defined as the ability of computer software and hardware to do those things that we, as humans, recognize as intelligent behaviour [120–125].

To demonstrate the efficiency and applicability of the proposed methods and for the purposes of comparison, various types of ED problems are examined. The results of this study show that the proposed approaches are able to find more economical loads than those determined by other methods.

V.2. EDP using Particle Swarm Optimization (PSO) :

In this section an efficient and particle swarm optimization (PSO) has been presented for solving the economic dispatch problem. The objective is to minimize the total generation fuel and keep the power outputs of generators, bus voltages and transformer tap setting in their secure limits. The conventional load flow and incorporation of the proposed method using PSO has been examined and tested for standard IEEE 30 bus system. The PSO method is demonstrated and compared with conventional OPF method (NR, Quasi Newton), and the intelligence heuristic algorithms such as genetic algorithm, evolutionary programming. The results show that PSO is an effective method to solve OPF problem.

V.2.1. Applied PSO to Optimal Power Flow :

To minimize the cost function F_T (II.2) is equivalent to getting a minimum fitness value in the searching process.

The particle that has lower cost function should be assigned a fitness value. The objective of OPF has to be changed to the maximization of fitness to be used as follows:

$$fitness = \begin{cases} F / f_{\max}; & if \quad f_{\max} > F \\ 0 \ ; & otherwise \end{cases}$$

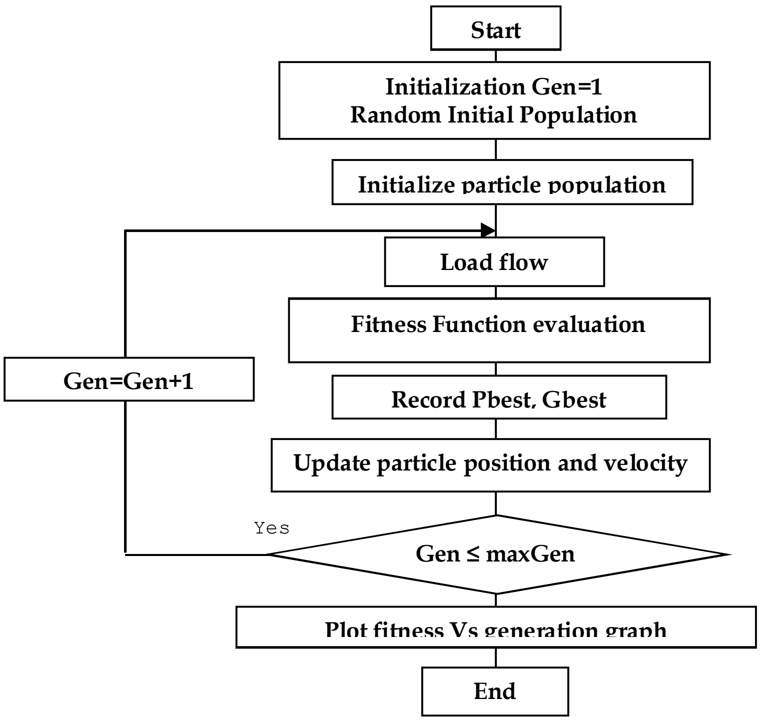


Figure V.1 : *PSO-OPF computational procedure.*

The PSO-based approach for solving the OPF problem to minimize the cost takes the following steps:

Step 1: randomly generated initial population.

Step 2: for each particle, the construction operators are applied.

Step 3: the Newton-Raphson routine is applied to each particle.

Step 4: fitness function evaluation.

Step 5: compare particles fitness function and determine P_{best} and G_{best}.

Step 6: change of particles velocity and position according to (IV.2) and (IV.3) respectively.

Step 7: if the iteration number reaches the maximum limit, go to Step 8. Otherwise, set iteration index k = k + 1, and go back to Step 2.

Step 8: print out the optimal solution to the target problem.

V.2.2. Load Flow Calculation :

Once the reconstruction operators have been applied and the control variables values are determined for each particle a load flow run is performed. Such flows run allows evaluating the branches active power flow, the total losses and voltage magnitude this will provide updated voltages angles and total transmission losses. All these require a fast and robust load flow program with best convergence properties; the developed load flow process is upon the full Newton Raphson algorithm.

V.2.3. Simulation Results And Discussion :

The proposed PSO algorithm is tested on standard IEEE 30 bus system shown in fig. V.2. The test system consists of 6 thermal units, 24 load buses and 41 transmission lines of which four of the branches (6-9), (6-10), (4-12) and (28-27) are with the tap setting transformer. The total system demand is 283.4 MW.

The optimal setting of the PSO control parameters are: c_1=0.5, c_2=0.5, numbers of particles is 50 and number of generations is 30; the Inertia weight was kept between 0.4 and 0.9.

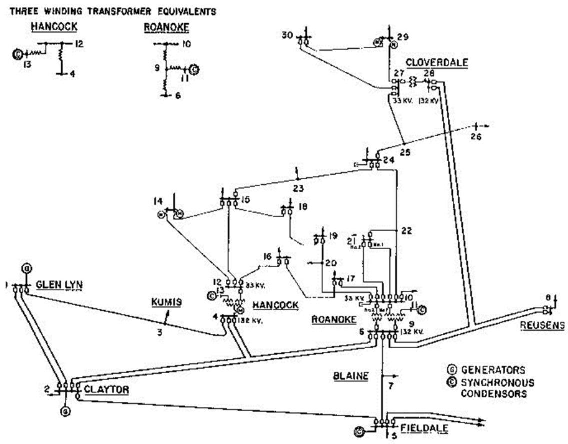


Figure V.2 : *IEEE 30-BUS Electrical Network.*

V.2.3.1. *Case 1: The OPF with quadratic fuel cost functions :*

In this case the units cost curves are represented by quadratic function. The generator cost coefficients are given in appendix.1 (A.1). The proposed PSO-OPF is applied to standard IEEE 30 bus system. The obtained results are given in tables V.1 and V.2.

Fig. V.3 shows the cost convergence of PSO based OPF algorithm for various numbers of generations. It was clearly shown that there is no rapid change in the fuel cost function value after 30 generations, hence it is clears from the figure that the solution is converged to a high quality solution at the early iterations (13 iterations).

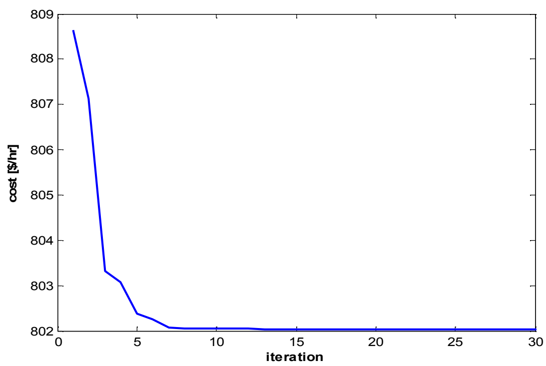


Figure V.3 : *Convergence characteristic of the IEEE 30 bus system.*

The minimize cost and power loss obtained by the proposed algorithm is less than value reported in [127, 128, 129] using the evolutionary techniques, genetic algorithm, Ant colony optimization for the some test systems. The results gotten including cost and power losses are compare with those acquired by others methods and present on tables V.1 and V.2.

Table V.1 : PSO-OPF compared with N.R and QN-OPF Methods for the IEEE 30-BUS system,

	N-R	QN-OPF	PSO-OPF
Pg_1 [MW]	99.211	170.237	175.6915
Pg_2 [MW]	80.00	44.947	48.6390
Pg_5 [MW]	50.00	28.903	21.4494
Pg_8 [MW]	20.00	17.474	22.7200
Pg_{11} [MW]	20.00	12.174	12.2302
Pg_{13} [MW]	20.00	18.468	12.0000
Power Loss [MW]	5.812	8.805	9.3301
Generation cost [$/hr]	901.918	807.782	802.0136

The results show that PSO algorithm gives much better results than the classical method. The difference in generation cost between these methods clearly shows the advantage of this method. In addition, it is important to point out that this simple PSO algorithm OPF converge in an acceptable time. For this system was converged to highly optimal solutions set after 13 generations.

Table V.2 : Comparison of the PSO-OPF with different evolutionary methods,

	IEP [127]	EP-OPF [128]	SADE_ALM [129]	PSO-OPF
Pg_1 [MW]	176.2358	173.8262	176.1522	175.6915
Pg_2 [MW]	49.0093	49.998	48.8391	48.6390
Pg_5 [MW]	21.5023	21.386	21.5144	21.4494
Pg_8 [MW]	21.8115	22.63	22.1299	22.7200
Pg_{11} [MW]	12.3387	12.928	12.2435	12.2302
Pg_{13} [MW]	12.0129	12.00	12.0000	12.0000
Power Loss [MW]	9.5105	9.3683	9.4791	9.3301
Generation cost [$/hr]	802.465	802.5557	802.404	**802.0136**

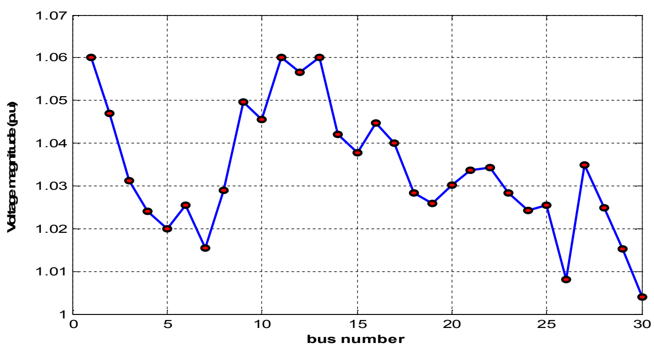


Figure V.4 : *The Voltages after optimization for the IEEE 30 bus system.*

The security constraints are also checked for voltage magnitudes and angles. Simulation results give the voltage magnitudes are from the minimum of 1.0040 p.u to maximum of 1.06 p.u. No load bus is under 1 pu (fig. V.4). The voltage angles are between a minimum value -14.065° and maximum value 0° (fig. V.5).

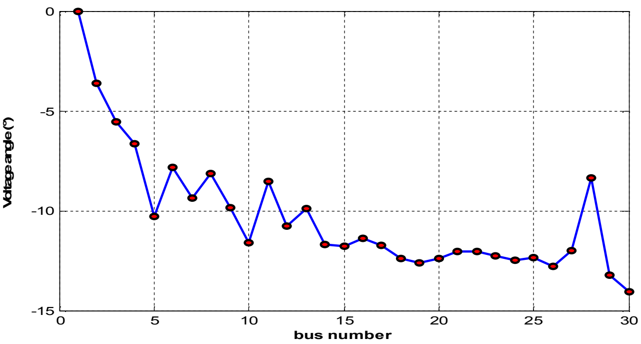


Figure V.5 : *The voltage angles after optimization for the IEEE 30 bus system.*

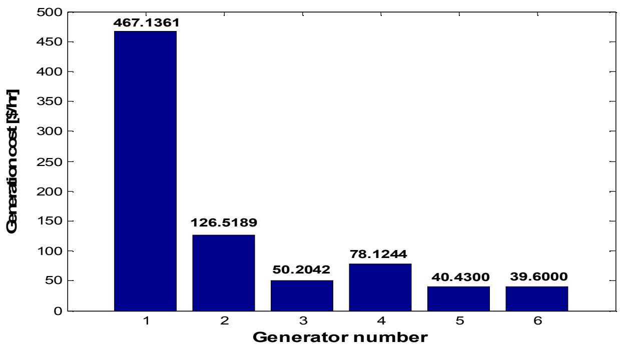
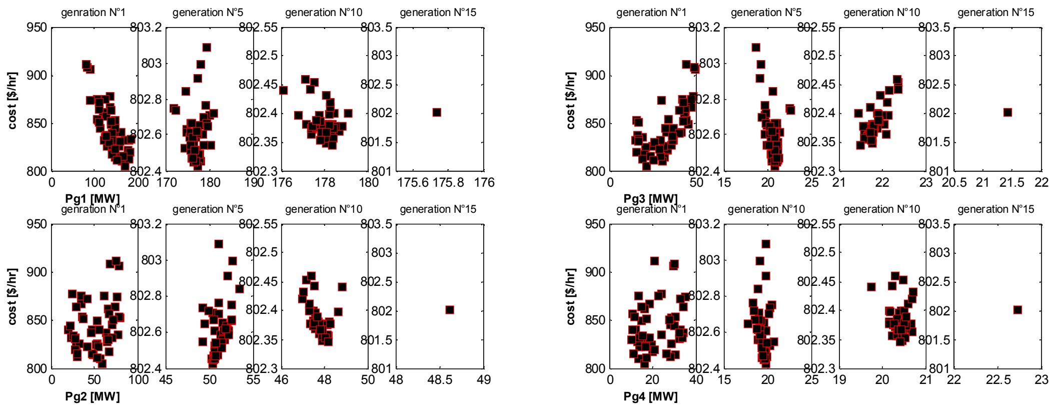


Figure V.6 : *Shows operating states of generating obtained by PSO based OPF algorithm.*



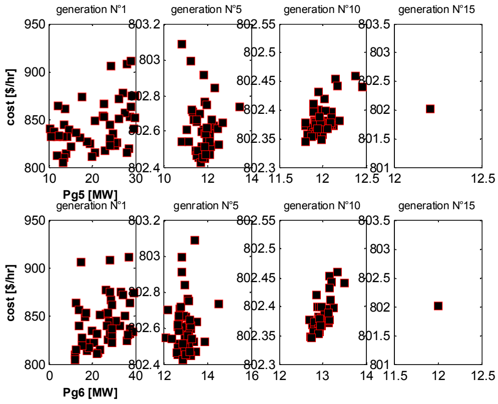


Figure V.7 : *Evolution of the fuel cost and the power generated during optimization.*

The evolution of the fuel cost function during the optimization process is shown in fig. V.7. It can be observed the production costs starts from the initial interval [800–950] \$/h. The optimal operating point has been obtained after 10 iterations. The optimal solution is achieved in 13 iterations as shown in fig. V.3.

V.2.3.2. *Case 2: The OPF for units with valve-point effects :*

In this case, the generator fuel cost curves of generator at bus 1 and 2 are represented by quadratic functions with rectified sine components using (eq. II.16). Bus 1 is selected as the slack bus of the system to allow more accurate control over units with discontinuities in cost curves. The generator cost coefficients of those two generators are given in appendix.1 (A.2). The simulation results are shown in table V.3 and the outer loop convergence characteristic is shown in fig. V.8.

Table V.3 : Comparison of the PSO-OPF with different evolutionary methods

	IEP [127]	SADE-ALM [129]	PSO-OPF
Pg_1 [MW]	149.7331	193.2903	199.6336
Pg_2 [MW]	52.0571	52.5735	20.0000
Pg_5 [MW]	23.2008	17.5458	22.2786
Pg_8 [MW]	33.4150	10.0000	29.5909
Pg_{11} [MW]	16.5523	10.0000	10.0000
Pg_{13} [MW]	16.0875	12.0000	12.0000
Power Loss [MW]	7.6458	12.0096	10.1031
Generation cost [\$/hr]	953.573	944.031	**920.9775**

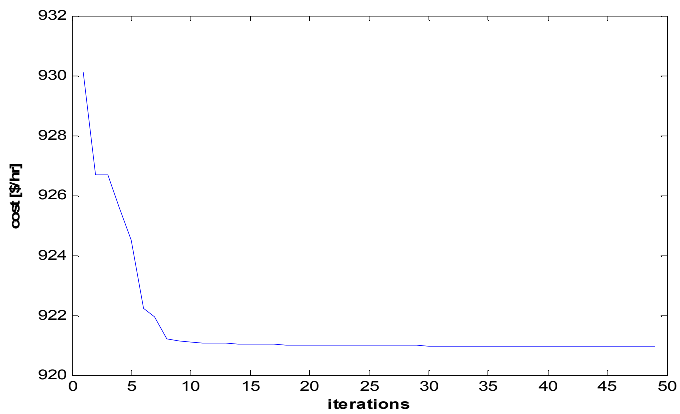


Figure V.8 : *Convergence plot with valve point effect.*

The problem economic problem takes into account valve point effect and cost function was modified equation (II.16). The losses were calculated using Newton raphson method for each iteration. Table V.3 summaries the results of the optimal settings as obtained by different methods. These results show that the optimal dispatch solution determined by the PSO lead to lower cost, which confirms that the PSO is well capable of determine the global or near global optimum dispatch solution.

It was found that the convergence of the method is fast and solution converges is less than 18 iterations.

PSO-OPF problem has been presented and applied to standard IEEE 30 bus system. The proposed algorithm has shown better result in terms of convergence and lesser generation cost, the results show that the optimal dispatch solutions determined by PSO lead to lower active power loss than that found by other methods, which confirms that the PSO is well capable of determining the global or near global optimum dispatch solution.

V.3. Pattern Search (PS) method to solve EDP :

In this section, a pattern Search method (PS) have been applied to the economic power dispatch EPD. The feasibility of the proposed method is to demonstrated and compared to those reported in the literature. The results are promising and show the effectiveness of the proposed method.

V.3.1. Simulation Results and Discussion :

The program has been developed and executed under Matlab system. The proposed PS algorithm is tested on standard on the standard IEEE 30 bus system consists of 6 thermal units (appendix.1 A.1).

Initially, several runs have been carried out with different values of the key parameters of PS such as the initial mesh size and the mesh expansion and contraction factors. In this study, the mesh size and the mesh expansion and contraction factor are selected as 1, 2 and 0.5, respectively. In addition, a vector of initial points, i.e. X_0, was randomly generated to provide an initial guess for the PS to proceed. As for the stopping criteria, all tolerances were set to 10^{-6} maximum number of iterations and function evaluations were set to 50.

The obtained results using PS based OPF are given in tables V.4 and fig. V.9. shows the cost convergence of PS based OPF algorithm for various numbers of generations. It was clearly shown that there is no rapid change in the fuel cost function value after 50 generations. Hence it is clears that the solution is converged to a high quality solution at the early iterations (25 iterations).

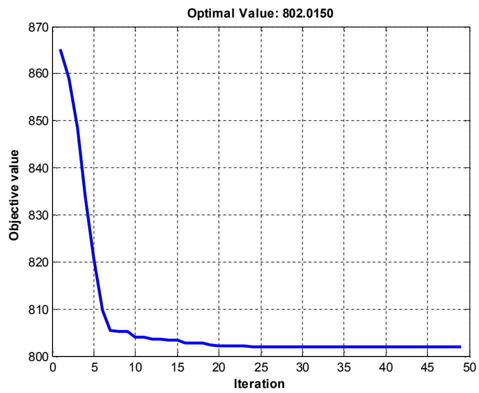


Figure V.9 : *Convergence of PS for the IEEE 30 bus system.*

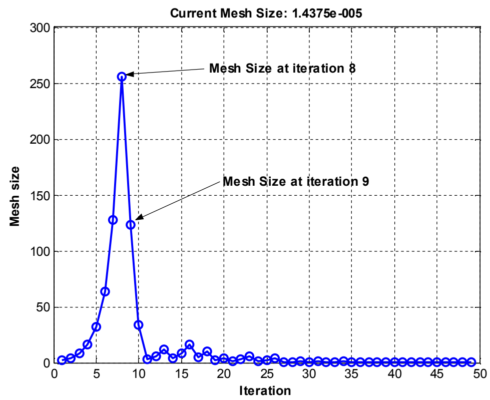


Figure V.10 : *Convergence of PS mesh size for the IEEE 30 bus system.*

The minimize cost and power loss obtained by the proposed algorithm is less than value reported in [126, 127, 128].

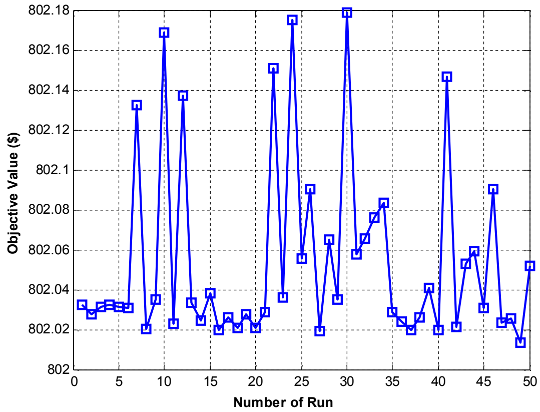


Figure V.11 : *Objective function value for 50 different starting point.*

Table V.4 : Comparison of the PSO-OPF with different evolutionary methods of optimization viewpoint cost, losses and times of convergence,

	IEP [127]	EP-OPF [128]	SADE-ALM [129]	PS
P_{g1} [MW]	176.2358	173.8262	176.1522	175.7276
P_{g2} [MW]	49.0093	49.998	48.8391	48.6812
P_{g5} [MW]	21.5023	21.386	21.5144	21.4282
P_{g8} [MW]	21.8115	22.63	22.1299	22.8313
P_{g11} [MW]	12.3387	12.928	12.2435	12.0667
P_{g13} [MW]	12.0129	12.00	12.0000	12.0000
Power Loss [MW]	9.5105	9.3683	9.4791	9.3349
Generation cost [$/hr]	802.465	802.5557	802.404	**802.0150**

The convergence of optimal solution using PS is shown in fig. V.9, where only about 25 iterations were needed to find the optimal solution. However, PS may be allowed to continue the search in the neighborhood of the optimal point to increase the confidence in the result. PS stops after 50 more iteration and returns the optimal value.

Fig. V.10 depicts the mesh size throughout the convergence process. It is apparent form the figure that the mesh size decreases until the algorithm terminates, in this case at mesh size 1.4375e-005 which is more that the giving as stopping criteria, thus indicating that this particular run did not terminate using the mesh size tolerance. Fig. V.10 shows that for the first 8 iteration the poll was successful since the mesh size keeps increasing as the algorithm had to expand the scope of the search. This is accomplished by multiplying the current mesh size by the expansion factor, in this study taken as 2. This scenario continued until iteration number 8 when the mesh size reached 256. At iteration number 9 the mesh size decreased by half due to multiplying the current mesh size by the contracting factor, indicating an unsuccessful poll in the previous iteration. This process continues until reaching one of the termination criteria.

It is worth mentioning that the mean and the maximum costs are higher than those of the other methods, and this is a certain drawback of the performance of PS in this test. Moreover, it has been observed that the algorithm is quite sensitive to the initial (starting) point and how far it is from the global optimal solution. Fig. V.11 illustrates the sensitivity of PS where a hundred solutions were obtained by PS with different initial values. The optimal solution has been reached a number of times for initial points around run number 49.

Pattern search (PS) have been studied and comparisons of the quality of the solution and performance have been conducted against evolutionary programming (IEP), (EP-OPF), and hybrid self-adaptive differential evolution methods (SADE-ALM).

V.4. Big Bang–Big Crunch algorithm to solve EDP :

A Big Bang–Big Crunch (BB–BC) optimization algorithm is employed for solving different types of ED problems. The proposed BB–BC algorithm has been examined and tested, the results obtained from the BB–BC algorithm have been compared to those that reported in the literature recently. The simulation results show that the proposed BB–BC algorithm approaches is able to obtain higher quality solutions efficiently and with less computational time than the conventional approaches.

V.4.1. Simulation Results and Discussion :

The proposed BB–BC algorithm method, it has been applied to solve various types of the ED problem on three different power systems (3 units, IEEE 30 standard bus and 15 units test system), and a comparison with other heuristic algorithms reported in the literature.

All methods are performed with 30 trials under the same evaluation function and individual definition in order to compare their solution quality, convergence characteristic and computation efficiency. In these examples. The software was implemented by the MATLAB language, on a Pentium 4, 2.4 GHz personal microcomputer with 1GB DDR RAM under Windows XP.

According to simulation, the following parameters in the BB-BC algorithms methods are used: The number of generation is 100 iterations and Size of population 50 individuals (candidates); the individual having minimum cost value is chosen for Big-Crunch phase; new population (Big Bang phase) is generated by using normal distribution principle with (eq. IV.11):

$$P_{Gi}^{k} = Pest_i + (P_{GiMax} - P_{GiMin}).rand / it \tag{V.1}$$

Where *k* number of candidates, *i* number of parameters, $Pest^k$ value which falls with minimum cost, P_{GiMax} and P_{GiMin} are parameter upper and lower limits and it number of iterations.

V.4.1.1. *Case 1: The OPF with quadratic fuel cost functions :*

A. Example 1

The proposed algorithm is tested on standard IEEE 30 bus system.

In this case, each individual P_g contains six generator power outputs, which are generated randomly. For 283.4 MW load demand, the best solutions, which are shown in table V.5, satisfy the system constraints. The statistical results obtained with 30 trials, such as the generation cost, computational time and Standard deviation are shown in table V.6.

Table V.5: Best solution of standard IEEE 30 Bus system

Unit power output	Methods			
	IEP [128]	EP-OPF [128]	SADE-ALM [129]	BB–BC
P_1 (MW)	176.2358	173.8262	176.1522	175.8299
P_2 (MW)	49.0093	49.998	48.8391	48.6122
P_5 (MW)	21.5023	21.386	21.5144	21.1692
P_8 (MW)	21.8115	22.63	22.1299	22.6083
P_{11} (MW)	12.3387	12.928	12.2435	12.5263
P_{13} (MW)	12.0129	12.00	12.0000	12.0000
Total P_g (MW)	292.9105	292.7683	292.8791	292.7460
P_{loss} (MW)	9.5105	9.3683	9.4791	9.346
Total cost ($/h)	802.465	802.5557	802.404	**802.0207**

Fig. V.12 shows the cost convergence of BB-BC based OPF algorithm for various numbers of generations. It was clearly shown that there is no rapid change in the fuel cost function value after 100 generations, clearly from the figure that the solution is converged to the best solution at the early iterations (45 iterations).

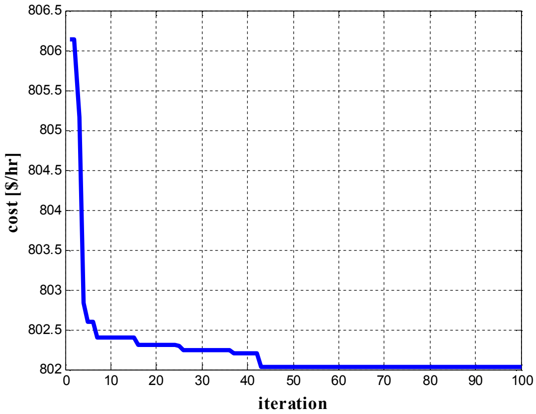


Figure V.12 : *Convergence characteristic of the IEEE 30 bus system.*

Table V.6 : Comparison of BB–BC performance with other methods.

Methods	Fuel Cost ($/hr.)				Average computational time (minutes)
	Best cost	Average cost	Worst cost	Standard deviation	
EP [128]	802.907	803.232	803.474	0.226	66.693
TS [128]	802.502	802.632	802.746	0.080	86.227
TS/SA [128]	802.788	803.032	803.291	0.187	62.275
ITS [128]	804.556	805.812	806.856	0.754	88.495
IEP [128]	802.465	802.521	802.581	0.039	99.013
SADE_ALM [129]	802.404	802.407	802.411	0.003	15.934
BB–BC	802.020	802.065	802.132	0.033	04.418

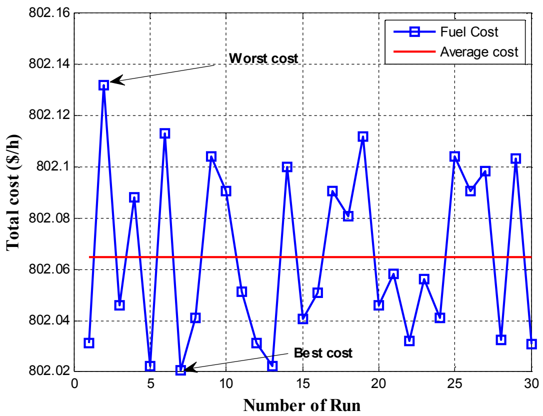


Figure V.13 : *Distribution of generation cost for IEEE 30 bus system.*

Or the IEEE 30 bus system, the best solutions of the seven methods are given in table V.6 after performing 30 trials. The results of the BB–BC based OPF algorithm are compared with those obtained by the EP, TS, TS/SA, ITS, IEP, and SADE-ALM algorithms in terms of Worst, Average, Best generation cost, the Standard deviation and Average computational time as shown in table V.6. Obviously, all methods have succeeded in finding the near optimum solution presented in [128], [129] with a high probability of satisfying the equality and inequality constraints.

Fig. V.13 shows distribution the generation cost of the best solution for each run in the case of 283.4 MW load demand.

B- Example 2

The system contains 15 thermal units [131] whose characteristics and the loss coefficients β matrices are given in appendix. 2. The load demand is 2630 MW.

In this case, each individual 15 generator power outputs, which are generated randomly. which are generated randomly. For 2630 MW load demand, the best solutions, which are shown in table V.7, satisfy the system constraints. The statistical results obtained with 30 trials, such as the generation cost, standard deviation, computational time and percentage of approaching near optimal solution, are shown in table V.8.

Fig. V.14. shows the cost convergence of BB–BC based OPF algorithm for various numbers of generations. It was clearly shown that there is no rapid change in the fuel cost function value after 100 generations. Hence it is clears from the Fig. V.14 that the solution is converged to a high quality solution at the early iterations (60 iterations).

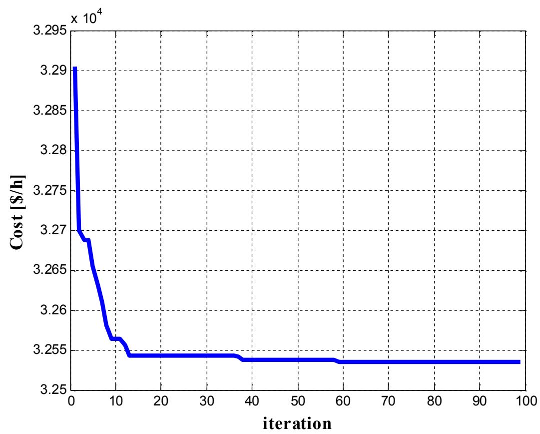


Figure V.14 : *Convergence characteristic of the 15 units system.*

Table V.7 : Best solution of 15 units system.

Unit power output	SA [130]	GA [130]	TS [130]	PSO [130]	MTS [130]	BB–BC
P_1 (MW)	453.6646	445.5619	453.5374	454.7167	453.9922	454.9991
P_2 (MW)	377.6091	380.0000	371.9761	376.2002	379.7434	455.0000
P_3 (MW)	120.3744	129.0605	129.7823	129.5547	130.0000	130.0000
P_4 (MW)	126.2668	129.5250	129.3411	129.7083	129.9232	130.0000
P_5 (MW)	165.3048	169.9659	169.5950	169.4407	168.0877	227.1366
P_6 (MW)	459.2455	458.7544	457.9928	458.8153	460.0000	460.0000
P_7 (MW)	422.8619	417.9041	426.8879	427.5733	429.2253	465.0000
P_8 (MW)	126.4025	97.8230	95.1680	67.2834	104.3097	60.0000
P_9 (MW)	54.4742	54.2933	76.8439	75.2673	35.0358	25.0000
P_{10} (MW)	149.0879	144.2214	133.5044	155.5899	155.8829	160.0000
P_{11} (MW)	77.9594	77.3002	68.3087	79.9522	79.8994	20.0000
P_{12} (MW)	73.9489	77.0371	79.6815	79.8947	79.9037	20.0000
P_{13} (MW)	25.0022	31.1537	28.3082	25.2744	25.0220	25.0000
P_{14} (MW)	16.0636	15.0233	17.7661	16.7318	15.2586	15.0000
P_{15} (MW)	15.0196	33.6125	22.8446	15.1967	15.0796	15.0000
Total output (MW)	2663.29	2661.23	2661.53	2661.19	2661.36	2662.13
P_{loss} (MW)	33.2737	31.2363	31.4100	31.1697	31.3523	32.1358
Total cost ($/h)	32786.40	32779.81	32762.12	32724.17	32716.87	**32659.35**

Table V.8 : Comparison of BB–BC performance with other methods.

Methods	Fuel Cost ($/hr.)				Average computational time (s)
	Best cost	Average cost	Worst cost	Standard deviation	
SA [130]	32786.40	32869.51	33028.95	112.32	71.25
GA [130]	32779.81	32841.21	33041.64	81.22	48.17
TSA [130]	32762.12	32822.84	32942.71	60.59	26.41
PSO [130]	32724.17	32807.45	32841.38	21.24	13.25
MTS [130]	32716.87	32767.21	32796.15	17.51	3.65
BB–BC	**32659.35**	32668.51	32673.02	2.69	12.65

For the 15 units system in the case of 2630 MW load demand, after performing 30 trials, the best solutions of the six methods are given in table V.7. The results of the BB-BC algorithm method in comparison with those of the SA, GA, TS, PSO and MTS [130] algorithms in terms of worst, average, best generation cost, standard deviation and average computational time are provided in table V.8.

From Figs. V.15–16 clearly, the BB–BC algorithm method has always better solutions than those of the other methods. This signifies the higher quality solution obtained by the proposed algorithm.

The simulation results in the IEEE 30 bus system and 15 units system demonstrate the feasibility and effectiveness of the proposed method BB-BC in minimizing cost of the generator. It is useful for obtaining high quality solution in a very less time compared to other methods EP, TS, TS/SA, ITS, IEP, SADE-ALM, SA, GA, TS, PSO and MTS.

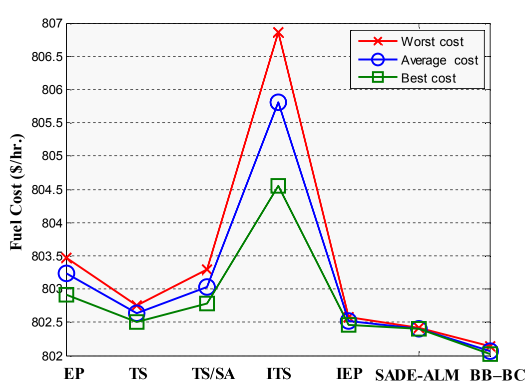


Figure 15 : *Comparison of BB–BC performance with other methods for IEEE 30 bus system.*

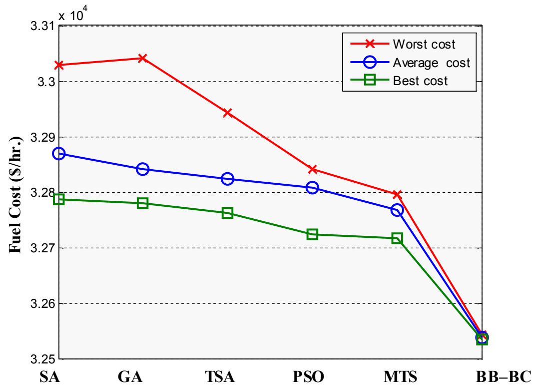


Figure 16 : *Comparison of BB–BC performance with other methods for 15 units system.*

The comparison of numerical results of optimal power flow (OPF) problems using the BB-BC method with the results obtained by other heuristic approaches are performed to demonstrate the robustness of the present algorithm. With respect to the BB–BC approach has better solutions and standard deviations.

The results show that the optimal dispatch solutions determined by BB-BC lead to lower active power loss then that found by other heuristic methods, which confirms that the BB-BC is well capable of determining the global or near global optimum dispatch solution.

The BB-BC optimization has several advantages over other evolutionary methods: Most significantly, a numerically simple algorithm and heuristic methods with relatively few control parameters; and the ability to solve problems that depend on large number of variables.

V.4.1.2. *Case 2: The OPF for units with valve-point effects*

In this case, the generator fuel cost curves of generator at bus 1 and 2 are represented by quadratic functions with rectified sine components using (II.16). Bus 1 is selected as the slack bus of the system to allow more accurate control over units with discontinuities in cost curves. The generator cost coefficients of those two generators are given in appendix. 1 (A.2).

The best solutions, which are shown in table V.9, satisfy the system constraints. The statistical results obtained with ten trials, such as the generation cost, computational time and Standard deviation are shown in table V.10.

Table V.9 : Best solution of standard IEEE 30 bus system

Unit power output	Methods		
	IEP [127]	SADE_ALM [129]	BB–BC
P_1 (MW)	149.7331	193.2903	199.6127
P_2 (MW)	52.0571	52.5735	20.0000
P_5 (MW)	23.2008	17.5458	21.7407
P_8 (MW)	33.4150	10.0000	26.2079
P_{11} (MW)	16.5523	10.0000	13.9545
P_{13} (MW)	16.0875	12.0000	12.0000
Total Pg (MW)	291.0458	295.4096	293.5158
P_{loss} (MW)	7.6458	12.0096	10.1158
Total cost ($/h)	953.573	944.031	**920.5089**

Fig. V.17 shows the cost convergence of BB–BC based OPF algorithm for various numbers of generations. It was clearly shown that there is no rapid change in the fuel cost function value after 100 generations, clearly that the solution is converged to a high quality solution at the 55 iterations.

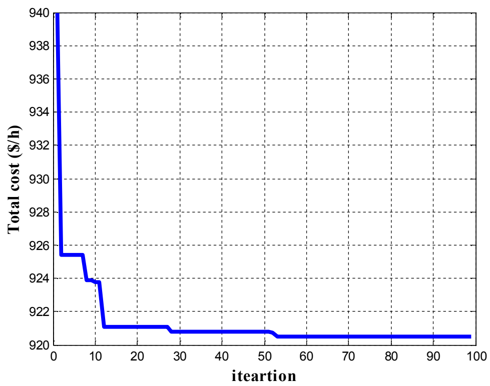


Figure V.178 : *Convergence characteristic of the IEEE 30 bus system (Case 2).*

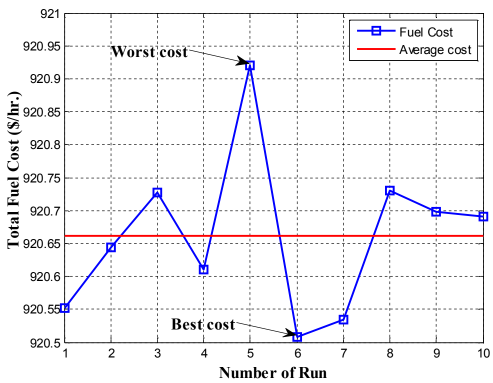


Figure V.18 : *Distribution of generation cost for IEEE 30 bus system (Case 2).*

For this case, the results from ten test runs of BB–BC do not violate any constraints. Table V.10 shows that worst, average, best generation cost, the standard deviation and average computational time of BB–BC are lower than those obtained by TS, TS/SA, ITS, EP, IEP and SADE-ALM.

Fig. V.18 shows distribution the generation cost of the best solution for each run in the case of 283.4 MW load demand.

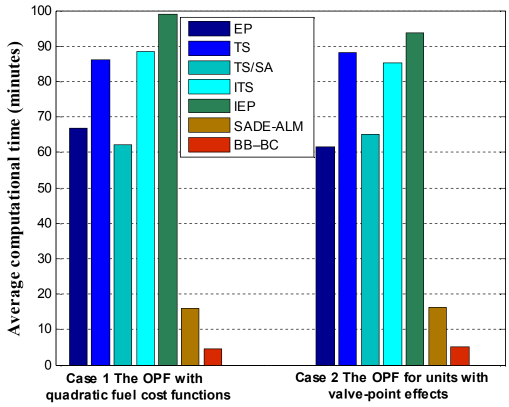


Figure V.19 : *Comparison of computation performance.*

The comparisons of computational time of the seven methods in the two cases are shown in fig. V.19. Clearly, the computational time of the MTS algorithm method is lowest in comparison to those of the other methods.

Table V.10 : Comparison of BB–BC performance with other methods

Methods	Fuel Cost ($/hr.)				Average computational time (minutes)
	Best cost	Average cost	Worst cost	Standard deviation	
EP [127]	955.508	957.709	959.379	1.084	61.419
TS [127]	956.498	958.456	960.261	1.070	88.210
TS/SA [127]	959.563	962.889	966.023	2.146	65.109
ITS [127]	969.109	977.170	985.533	6.191	85.138
IEP [127]	953.573	956.460	958.263	1.720	93.583
SADE-ALM [129]	944.031	954.800	964.794	5.371	16.160
BB–BC	920.508	920.661	920.920	0.121	5.0472

The simulation results in the IEEE 30 bus system demonstrate the feasibility and effectiveness of the proposed method BB-BC in minimizing cost of the generator. It is useful for obtaining high quality solution in a very less time compared to other methods EP, TS, TS/SA, ITS, IEP and SADE-ALM.

The comparison of numerical results of optimal power flow (OPF) problems with valve-point effects using the BB–BC method with the results obtained by other heuristic approaches are performed to demonstrate the robustness of the present algorithm.

V.4.1.3. *Case 3: A multi-objective BB–BC for environmental/economic dispatch*

The Combined Economic and Emission Dispatch (CEED) problem where objective function is highly non-linear, non-differentiable and may have multiple local minima. Therefore, classical optimization methods may not converge or get trapped to any local minima. In this case presents a BB-BC method to solve the combined economic and emission dispatch (CEED), three generator test system was used for testing and validation purposes, the preference of the BB-BC is compared with other heuristic methods. The results show, clearly, that the proposed method gives better optimal solution as compared to the other methods.

During the simulation, the following parameters in the BB–BC algorithms methods are used :

The number of generation is 100 iterations and size of population 50 individuals (candidates),

The individual having minimum cost value is chosen for Big-Crunch phase,

New population (Big Bang phase) is generated by using normal distribution principle.

The proposed BB–BC algorithm is tested on three generator test system whose data are given below [132], The values of fuel cost and emission coefficients are taken from reference [133] and are given in appendix.3. The system demand is 850 [MW] in all simulations

The system transmission losses is calculated using a simplified loss expression:

$$P_L = 0.00003P_{G1}^2 + 0.00009P_{G2}^2 + 0.00012P_{G3}^2 \text{ MW}$$

Table V.11 : Solutions of minimum fuel cost.

Evolutionary Algorithms	BB_BC	Tabu Search [133]	NSGA-II [132]
P_1 [MW]	434.5152	435.69	436.366
P_2 [MW]	300.7308	298.828	298.187
P_3 [MW]	130.6044	131.28	131.228
Losses [MW]	15.8505	15.798	15.781
Fuel cost [$/h]	**8344.5952**	**8344.598**	**8344.606**
SO_2 Emission [Kg/h]	9.02261	9.02146	9.02083
NO_x Emission [Kg/h]	0.09871	0.09870	0.09866

In this study, a developed algorithm has been applied for bi-objective fuel cost , SO_2 emission dispatch and NO_x emission dispatch. The results for best fuel cost, best SO_2 emission and NO_x emission dispatch are summarized in tables V.11 to V.13. Correspondingly, the convergence for optimized objective functions are shown in figures V.20 to V.22, respectively.

Table V.12 : Solutions of minimum SO2 Emission.

Evolutionary Algorithms	BB_BC	Tabu Search [133]	NSGA-II [132]
P_1 [MW]	552.7414	549.247	541.308
P_2 [MW]	219. 0790	234.582	223.249
P_3 [MW]	92.6958	81.893	99.919
Losses [MW]	14.5164	15.722	14.476
Fuel cost [$/h]	8397.023	8403.485	8387.518
SO_2 Emission [Kg/h]	**8.965936**	**8.874**	**8.96655**
NO_x Emission [Kg/h]	0.09684	0.09740	0.09637

Table V.13 : Solutions of minimum NOx Emission

Evolutionary Algorithms	BB_BC	Tabu Search [133]	NSGA-II [132]
P_1 [MW]	508.291	502.914	505.810
P_2 [MW]	250.600	254.294	252.951
P_3 [MW]	105.854	108.592	106.023
Losses [MW]	14.747	15.8	14.784
Fuel cost [$/h]	8364.953	8371.143	8363.627
SO_2 Emission [Kg/h]	8.965936	8.874	8.96655
NO_x Emission [Kg/h]	**0.09592**	**0.0958**	**0.09593**

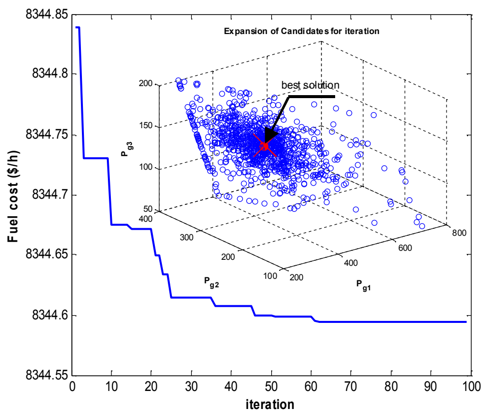


Figure V.20 : *Convergence characteristic of minimum fuel cost.*

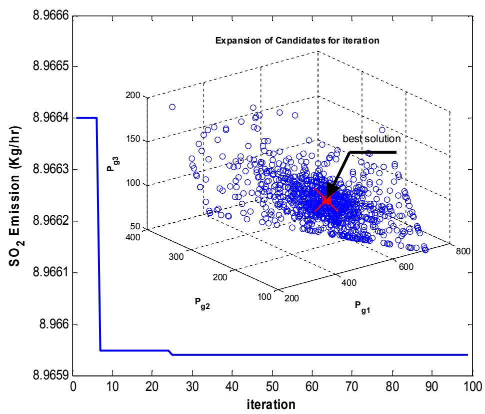


Figure V.21 : *Convergence characteristic of minimum SO2 Emission.*

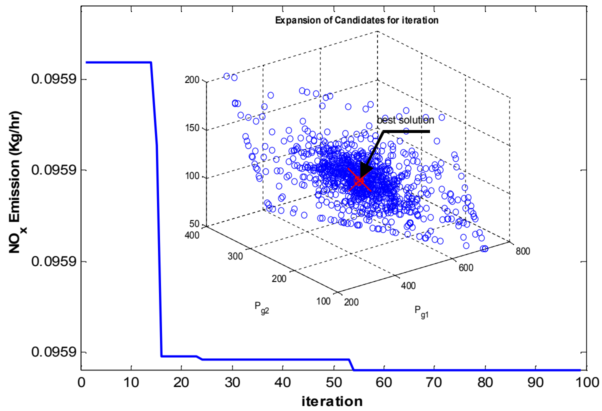


Figure V.22 : *Convergence characteristic of minimum NO_x Emission.*

The figures V.20 to V.22 show the minimum fuel cost, SO_2 Emission and *NOx* Emission convergence of BB–BC algorithm for various numbers of generations. It was clearly shown that there is no great change in the fuel cost function value after 100 generations.

The best compromise solution selected using BB–BC algorithm is shown in table V.14.

Table V.14 : Best compromise solution.

Evolutionary Algorithms	**BB-BC**
P_1 **[MW]**	442.893
P_2 **[MW]**	305.503
P_3 **[MW]**	117.546
Losses [MW]	15.94
Fuel cost [$/h]	8345.813
SO_2 Emission [Kg/h]	9.01602
NO_x Emission [Kg/h]	0.09776
Cost total ($/h)	**25035.140**

The simulation results in the test system demonstrate the feasibility and effectiveness of the proposed method BB-BC in minimizing the operating cost of the generators. It is useful to compare the BB-BC technique to other methods such as tabu search [133] and NSGA-II [132] for obtaining and demonstrating high quality solution and validating our results.

V.5. ABC optimization for economic dispatch with valve point effect :

In this section we presents the well-known power system ED problem solution considering valve-point effect by a new optimization algorithm called artificial bee colony (ABC). The proposed approach has been applied to various test systems with incremental fuel cost function, taking into account the valve-point effects. The results show that the proposed approach is efficient and robustness when compared with other optimization algorithms reported in literature.

In order to verify the feasibility and efficiency of the proposed algorithm, three tests were conducted for solving ED problem with valve-point effects, which are 3, 13 and 40 unit systems ignoring the transmission loss, including valve-point loading.

The algorithm of this method was programmed in MATLAB 2011Ra environment and run on a PC with Intel core i3 1.90. GHZ PC and 4 GB of RAM.

V.5.1. Test system 1: small system (3-unit system) :

This test case study considering three thermal units of generation with effects of valve-point is given in appendix. 4 **(**A.7**)** [134]. In this case, the load demand expected to be determined was P_D= 850 MW.

Table V.15 : Results obtained by proposed method for test system 1.

Units	Proposed ABC
1 power output/MW	300.2656
2 power output/MW	149.7344
3 power output/MW	400.0000
Total power output/MW	850.000
Total cost/($\$\cdot h^{-1}$)	8234.07245

Table V.16 : Comparison of proposed method for test system 1.

Method	P_1/MW	P_2/MW	P_3/MW	P_D/MW	Cost/($\$\cdot h^{-1}$)
GA [134]	398.700	50.100	399.600	848.400	8222.07
EP [134]	300.264	149.736	400.000	850.000	8234.07
EP-SQP [134]	300.267	149.733	400.000	850.000	8234.07
PSO [134]	300.268	149.732	400.000	850.000	8234.07
PSO-SQP [134]	300.267	149.733	400.000	850.000	8234.07
GAB [135]	—	—	—	—	8234.08
GAF [135]	—	—	—	—	8234.07
CEP [135]	—	—	—	—	8234.07
FEP [135]	—	—	—	—	8234.07
MFEP [135]	—	—	—	—	8234.08
IFEP [135]	—	—	—	—	8234.07
PS [136]	300.2663	149.7331	399.9996	849.9990	8234.05
GSA [137]	300.2102	149.7953	399.9958	850.0013	8234.1
Proposed ABC	300.2656	149.7344	400.0000	850.000	**8234.07245**

The simulation parameters for the proposed algorithm are: colony size (employed bees + onlooker bees) = 20, food sources = 10, limit=100, and max iterations=500.

The results obtained for this case study are listed in table V.15, which shows that the ABC algorithm has approximately good solution for the power demand of 850 MW. The best fuel cost result obtained from the proposed ABC algorithm and other optimization algorithms are compared in table V.16. From table V.16 it is seen clearly that the GA and PS approaches did not meet the load demand.

A convergence characteristic of the ABC algorithm for the three generator systems shown in Figs V.23 and V.24 shows the distribution of the generation cost of the best solution for each run in the test system of 3 units.

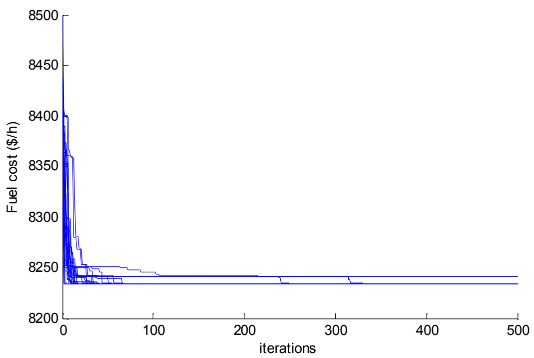


Figure V.23 : *Convergence of fitness value with valve-point effects for load demand 850 MW.*

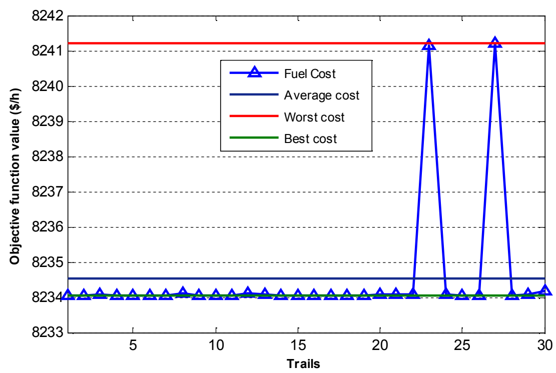


Figure V.24 : *Distribution of objective function value for 30 trails.*

V.5.2. Test system 2: 13-unit system :

This test case study considering the thirteen thermal units of generation with effects of valve-point is given in appendix. 4 (A.8) [138, 135].

The complexity and nonlinearity to solution procedure is increased. The required load demands to be met by all the thirteen generating units are 1800 and 2520 MW.

The results obtained for this case study are given in tables V.17 and V.18, which show that the simulation results obtained by the ABC algorithm for the best solution for power demand of 1800 and 2520 MW respectively.

Simulation parameters: colony size = 200, food sources = 100, limit=100, and max iterations=1000.

The best fuel cost result obtained from the proposed ABC algorithm and other optimization algorithms are compared in tables V.19 and V.20 for the load demand of 1800 and 2520 MW respectively. It appears that the proposed algorithm performs better as the problem becomes larger and more complex. Figs. V.25 and V.27 show the convergence characteristic curves of the best case with valve point effect for the load demand of 1800 and 2520 MW respectively.

Table V.17 : Results obtained by proposed method for test system 2 (1800 MW).

Units	Proposed ABC	Units	Proposed ABC
1 power output/MW	628.2772	9 power output/MW	109.8263
2 power output/MW	148.8823	10 power output/MW	40.0000
3 power output/MW	223.6160	11 power output/MW	40.0000
4 power output/MW	60.0000	12 power output/MW	55.0000
5 power output/MW	109.8531	13 power output/MW	55.0000
6 power output/MW	109.8395	Total power output/MW	1800.0099
7 power output/MW	109.8605	Total cost/($\$\cdot h^{-1}$)	**17962.4279**
8 power output/MW	109.8550		

Table V.18 : Results obtained by proposed method for test case 2 (2520 MW).

Units	Proposed GSA	Units	Proposed GSA
1 power output/MW	628.3119	9 power output/MW	159.7309
2 power output/MW	298.9825	10 power output/MW	77.2108
3 power output/MW	295.7710	11 power output/MW	77.0372
4 power output/MW	159.7329	12 power output/MW	92.2275
5 power output/MW	159.7318	13 power output/MW	92.0833
6 power output/MW	159.7293	Total power output/MW	2520.0092
7 power output/MW	159.7324	Total cost/($\$\cdot h^{-1}$)	**24166.2199**
8 power output/MW	159.7277		

Table V.19 : Comparison of proposed method for test system 2 (1800 MW).

Method	Total cost/($\$\cdot h^{-1}$)	Method	Total cost/($\$\cdot h^{-1}$)
CEP [135]	18048.21	UHGA [140]	17964.81
PSO [134]	18030.72	QPSO [141]	17964
MFEP [135]	18028.09	IGA_MU [135]	17963.98
FEP [135]	18018.00	ST-HDE [115]	17963.89
IFEP [135]	17994.07	HGA [142]	17963.83
EP-SQP [134]	17991.03	HQPSO(5) [134]	17963.9571
HDE [115]	17975.73	DE [143]	17963.83
CGA-MU [139]	17975.34	GSA [137]	17960.3684
PSO-SQP [134]	17969.93	Proposed ABC	**17962.4279**
PS [136]	17969.17		

Table V.20 : Comparison of proposed method for test case 2 (2520 MW).

Method	Total cost/($\$\cdot h^{-1}$)	Method	Total cost/($\$\cdot h^{-1}$)
SA[134]	24970.91	IGAMU [144]	24169.979
GA [134]	24398.23	HGA [142]	24169.92
GA-SA[134]	24275.71	EDSA[135]	24169.92
EP-SQP [134]	24266.44	DE [143]	24169.9177
PSO-SQP[134]	24261.05	GSA [137]	24164.251357
UHGA [140]	24172.25	Proposed	**24166.2199**
GA-MU [144]	24170.755		

Figures V.26 to V.28 shows the distribution of the generation cost of the best solution value for 30 trails for the load demand of 1800 and 2520 MW respectively.

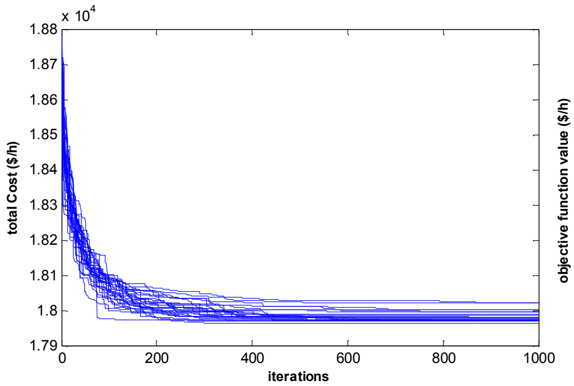


Figure V.25 : Convergence of fitness value with valve-point effects for load demand 1800 MW.

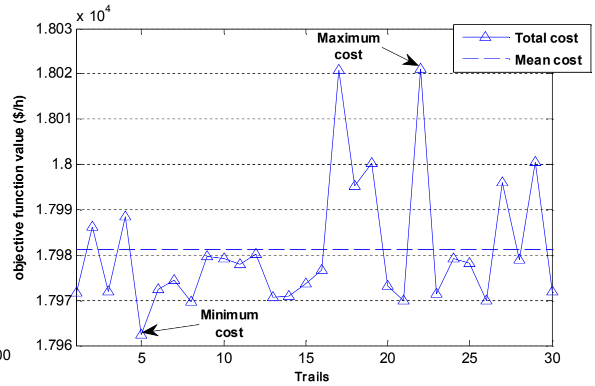


Figure V.26 : Distribution of objective function value for 30 trails.

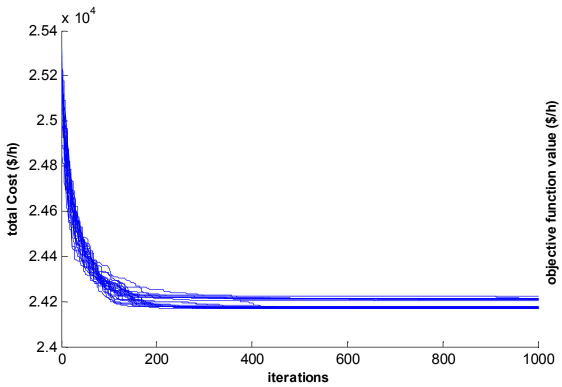


Figure V.27 : Convergence of fitness value with valve-point effects for load demand 2520 MW.

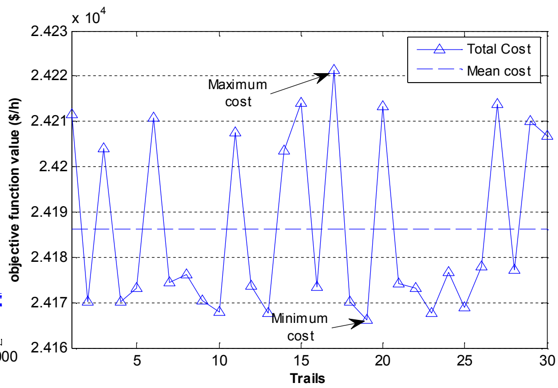


Figure V.28 : Distribution of objective function value for 30 trails.

V.5.3. Test system 3: large system (40-unit system)

This test system consists of 40 generators with valve-point loading effects and has a total load demand of 10500 MW. The input data are given in ref. [135]. The result obtained from the proposed ABC algorithm has been compared with NPSO-LRS [145], MDE [146], and other methods. The best solutions are tabulated in table V.21 and the performance parameters are compared in table V.22. A convergence characteristic of the 40-generator systems in case of the ABC algorithm is demonstrated in figs. V.29 and V.30 shows the distribution of the generation cost of the best solution for each run in the test system of 40-units.

Simulation parameters: colony size (employed bees + onlooker bees) = 200, food sources = 100, limit=100, and max iterations=1000.

Table V.21 : Best power output for 40-generator system (Load=10500 MW)

Generator power output	ABC	NPSO_LRS[145]	NPSO[145]	MDE[146]	CBPSO-RVM[147]	FAPSO-NM[148]
P_{g1}/MW	110.7944	113.9761	113.9891	110.831	114	111.38
P_{g2}/MW	110.7913	113.9986	113.6334	110.815	114	110.93
P_{g3}/MW	97.4473	97.4241	97.55	97.399	97.4859	97.41
P_{g4}/MW	179.7417	179.7327	180.0059	179.734	179.7331	179.33
P_{g5}/MW	87.8268	89.6511	97	87.808	97	89.22
P_{g6}/MW	139.9897	105.4044	140	140	140	140
P_{g7}/MW	259.5761	259.7502	300	259.6	300	259.62
P_{g8}/MW	284.5962	288.4534	300	284.604	300	284.66
P_{g9}/MW	284.5294	284.646	284.5797	284.601	286.0079	284.66
P_{g10}/MW	130.0033	204.812	130.0517	130	130	130
P_{g11}/MW	168.7903	168.8311	243.7131	168.799	94	168.82
P_{g12}/MW	94.0010	94	169.0104	168.799	94	168.82
P_{g13}/MW	215.4183	214.7663	125	214.759	214.7598	214.75
P_{g14}/MW	394.2843	394.2852	393.9662	394.28	304.5196	394.28
P_{g15}/MW	394.2274	304.5187	304.7586	394.28	394.2794	304.54
P_{g16}/MW	394.1741	394.2811	304.512	304.519	394.2794	394.3
P_{g17}/MW	489.2802	489.2807	489.6024	489.279	489.2794	489.29
P_{g18}/MW	489.2863	489.2832	489.6087	489.28	489.2794	489.29
P_{g19}/MW	511.2606	511.2845	511.7903	511.28	511.2794	511.28
P_{g20}/MW	511.2471	511.3049	511.2624	511.279	511.2794	511.29
P_{g21}/MW	523.3126	523.2916	523.3274	523.279	523.2796	523.33
P_{g22}/MW	523.2619	523.2853	523.2196	523.28	523.2794	523.48
P_{g23}/MW	523.2069	523.2797	523.4707	523.28	523.2797	523.33
P_{g24}/MW	523.2790	523.2994	523.0661	523.28	523.2802	523.33
P_{g25}/MW	523.2828	523.2865	523.3978	523.281	523.2795	523.33
P_{g26}/MW	523.2828	523.2936	523.2897	523.279	523.2794	523.33
P_{g27}/MW	10.0035	10	10.0208	10	10	10
P_{g28}/MW	10.0601	10.0001	10.0927	10	10	10
P_{g29}/MW	10.0063	10	10.0621	10	10	10
P_{g30}/MW	88.0050	89.0139	88.9456	92.645	97	88.7
P_{g31}/MW	189.8676	190	189.9951	190	190	190
P_{g32}/MW	189.9970	190	190	190	190	190
P_{g33}/MW	179.4734	190	190	189.999	190	190
P_{g34}/MW	164.8527	199.9998	165.9825	164.831	200	165
P_{g35}/MW	164.8280	165.1397	172.4153	164.802	166.8603	166
P_{g36}/MW	164.8093	172.0275	191.2978	164.805	200	165
P_{g37}/MW	109.9733	110	109.9893	109.999	110	110
P_{g38}/MW	109.9999	110	109.9521	109.999	110	110
P_{g39}/MW	109.9544	93.0962	109.8733	109.999	110	110
P_{g40}/MW	511.2777	511.2996	511.5671	511.278	511.2794	511.3
Total cost/($\$\cdot h^{-1}$)	**121479.6467**	121664.43	121704.73	121414.79	121555.32	121418.3

Table V.22 : Comparison of results case 2 load=10500 MW.

Method	Minimum cost/$(\$\cdot h^{-1})$	Mean cost/$(\$\cdot h^{-1})$	Maximum cost/$(\$\cdot h^{-1})$	Mean time/s
CEP [135]	123488.29	124793.5	126902.9	1956.9
FEP [135]	122679.71	124119.4	127245.6	1039.1
MFEP [135]	122647.57	123489.7	124356.5	2196.1
IFEP [135]	122624.35	123382.0	125740.6	1167.3
NPSO-LRS [145]	121664.43	122209.31	122981.59	19.8
MDE [146]	121414.79	121418.44	121466.04	-
GA [146]	121996.40	123807.97	122919.77	320.31
CBPSO-RVM[147]	121555.32	122281.14	123094.98	—
PS [29]	121415.14	122332.7	125486.3	42.98
FAPSO-NM [148]	121418.3	121418.80	121419.8	40
EP-SQP[134]	122323.97	122379.6	—	997.73
PSO [134]	123930.45	124155	—	933.39
PSO-SQP [134]	122094.67	122245.3	—	733.97
MPSO[149]	122252.27	—	—	—
ESO[150]	122122.16	122524.1	123143.1	—
DEC(2)-SQP(1) [138]	121741.98	122295.1	122839.3	14.26
TM [151]	122477.78	123078.2	124693.8	94.28
APSO [152]	121663.52	122153.67	122912.39	5.05
TS [153]	122288.38	122590.89	122424.81	238.35
ACO [153]	121811.37	121930.58	122048.06	92.54
ABC	**121479.6467**	121984.24	122137.42	**16.52**

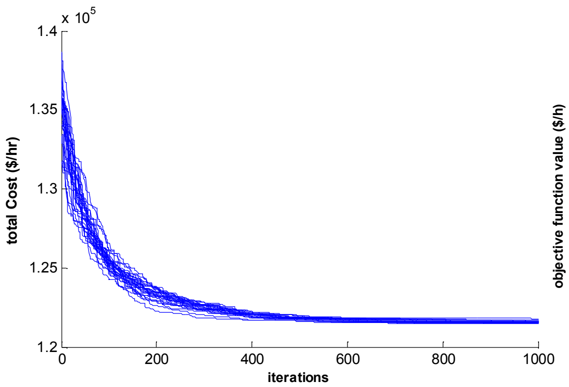


Figure V.29 : *Convergence of fitness value with valve-point effects for load demand 2520 MW.*

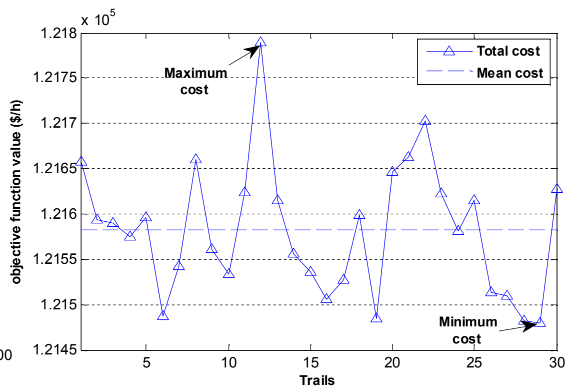


Figure V.30 : *Distribution of objective function value for 30 trails.*

The comparison confirms the effectiveness, stable convergence characteristic, good computation efficiency and superiority of the proposed ABC algorithm over the other techniques in terms of solution quality.

However good choice of the number of iterations, population size, employed and unemployed bees results in fast computation. The ABC can be modified using operators of fast computational algorithms to get a hybrid fast computational ABC. The simulation results reveal the superiority of the proposed technique in solving the DED problem with valve point effects. Therefore, this approach could also be extended to other optimization and control problems of power systems.

V.6. A hybrid GA–PS method to Solve the EDP :

In his study we presents a new approach based on a hybrid algorithm consisting of genetic algorithm (GA) and pattern search (PS) techniques for solving the economic load dispatch (ELD) problem. The objective is to minimize the nonlinear function, which is the total fuel cost of thermal generating units, subject to the usual constraints. GA is the main optimizer of the algorithm, whereas PS are used to fine tune the results of GA to increase confidence in the solution. For illustrative purposes, the algorithm has been applied to various test systems to assess its effectiveness. Furthermore, convergence characteristics and robustness of the proposed method have been explored through comparison with results reported in literature. The outcome is very encouraging and suggests that the hybrid GA–PS algorithm is very efficient in solving power system economic dispatch problem.

The main objective is to introduce a hybrid method that combines the GA and PS - referred to as the hybrid GA–PS method- in the context of power system economic dispatch problem. The proposed hybrid method has eliminated the need to provide a suitable starting point for PS, this feature led to the reduction of total execution time of the algorithm when compared to other reported methods, a the hybrid GA–PS method is presented and used to solve the ELD problem under some equality and inequality constraints, an application was performed on the IEEE 30 bus and 6 generators test system. Simulation results confirm the advantage of computation rapidity and solution accuracy.

The obtained results using hybrid GA–PS algorithm OPF are given in tables V.23.

The parameters of GA : the number of generation is 100 iterations and population size is 30 invidious with probability of crossover $P_c = 0.9$ and mutation $P_m = 0.03$.

Fig. V.31 shows the cost convergence of hybrid GA–PS algorithm for various numbers of generations. It was clearly shown that there is no rapid change in the fuel cost function value after 50 generations, clearly that the solution is converged to a high quality solution at the early iterations (25 iterations).

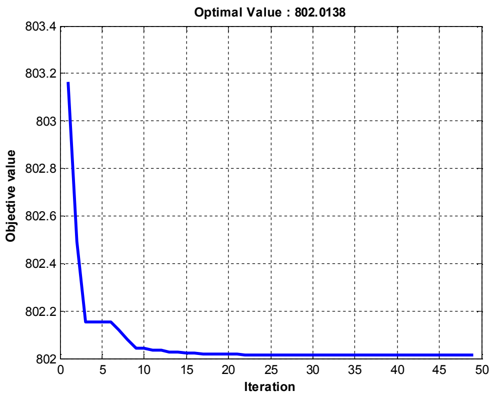


Figure V.31 : *Convergence of PS for the IEEE 30 bus system.*

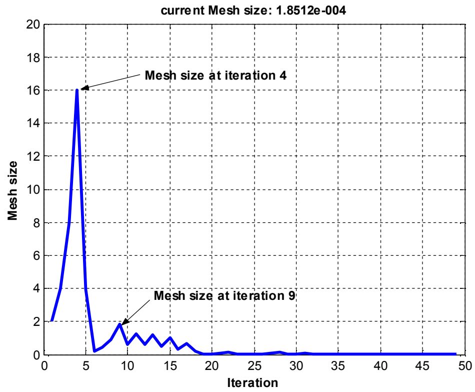


Figure V.32 : *Convergence of PS mesh size for the IEEE 30 bus system.*

The minimize cost and power loss obtained by the proposed algorithm is less than value reported in [128-129].

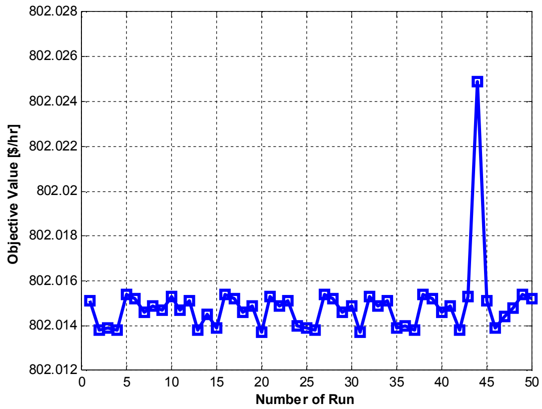


Figure V.33 : *Objective function value for 50 different starting point.*

Table V.23 : Comparison of the PSO-OPF with different evolutionary methods of optimization viewpoint cost, losses and times of convergence.

	IEP [128]	EP-OPF [128]	SADE-ALM [129]	**PS**	**GA-PS**
P_{g1} [MW]	176.2358	173.8262	176.1522	175.7276	75.6627
P_{g2} [MW]	49.0093	49.998	48.8391	48.6812	48.6413
P_{g5} [MW]	21.5023	21.386	21.5144	21.4282	21.4222
P_{g8} [MW]	21.8115	22.63	22.1299	22.8313	22.6219
P_{g11} [MW]	12.3387	12.928	12.2435	12.0667	12.3806
P_{g13} [MW]	12.0129	12.00	12.0000	12.0000	12.0000
Power Loss [MW]	9.5105	9.3683	9.4791	9.3349	9.3286
Generation cost [$/hr]	802.465	802.5557	802.404	802.0150	**802.0138**

Fig. V.32 depicts the mesh size throughout the convergence process. It is apparent form the figure that the mesh size decreases until the algorithm terminates, in this case at mesh size 1.8512e-004 which is more that the giving as stopping criteria, thus indicating that this particular run did not terminate using the mesh size tolerance. Fig. V.33 illustrates the sensitivity of PS where a hundred solutions were obtained by PS with different initial values. The optimal solution has been reached a number of times for initial points around run number 50.

The GA-PS technique has overcome an important drawback of the PS methods that is the need to supply a suitable starting point, this shortcoming of the PS methods was highlighted in the previous work of the authors as it makes any optimization method relying on a good choice of the initial point possibly more susceptible to getting trapped in local minima, although the much improved speed of computation allows for additional searches to be made to increase the confidence in the solution. The hybrid GA-PS algorithm, on the other hand, does not require the user to specify the starting point as it is generated automatically for the PS stage by the initial GA phase. Moreover, the performance of the proposed hybrid method improves with the increase of size and complexity of the system. Overall, the proposed algorithm has been shown to perform extremely well for solving economic dispatch problems.

V.7. A HBB–BC optimization algorithm for solving the Different EDP :

In this section, we applied a Hybrid Big Bang–Big Crunch (HBB–BC) optimization algorithm technique for solving the different economic load dispatch (ELD) problems in power systems. Many nonlinear characteristics of the generator, such as ramp rate limits, prohibited operating zone, and non-smooth cost functions are considered using the proposed method in practical generator operation. The feasibility of the proposed method is demonstrated for three different systems, and it is compared with Big Bang–Big Crunch (BB–BC) method and other optimization methods. The experimental results show that the proposed HBB–BC method was indeed capable of obtaining higher quality solutions efficiently in ELD problems.

A Hybrid Big Bang–Big Crunch (HBB–BC) Optimization method has been employed to solve economic dispatch problem. The HBB–BC method consists of two phases: a Big Bang phase where candidate solutions are randomly distributed over the search space, and a Big Crunch phase working as a convergence operator where the center of mass is generated. Then new solutions are created by using the center of mass to be used as the next Big Bang [154] .These successive phases are carried repeatedly until a stopping criterion has been met. This algorithm not only considers the center of mass as the average point in the beginning of each Big Bang ,but also similar to Particle Swarm Optimization-based approaches [6], utilizes the best position of each particle and the best visited position of all particles. As a result because of increasing the exploration of the algorithm, the performance of the BB–BC approach is improved [154].

The proposed approach has been applied to various test systems, and the results show that performance of the proposed approach reveal the efficiently and robustness when with the classical BB–BC method and other optimization algorithms reported in literature in the solution quality and computation efficiency.

V.7.1. Applying the HBB–BC to the ED problem :

In this section the proposed algorithm is applied to solve the economic dispatch problem. To apply the HBB–BC, the following steps have to be taken [155].

Step.1. Define the input data

In this step, the input data including the cost coefficients of the generators, output generator constraints, transmission loss matrix coefficients and loads, the number of iterations ($Iter_{max}$), the size of the population (candidates) and the adjustable parameters α_1, α_2 and α_3.

Step.2. Generate the initial population.

Initialize randomly the individuals of the population according to the limit of each unit including individual dimensions. These initial individuals must be feasible candidate solutions that satisfy the practical operation constraints.

Step.3. To each individual P_{Gi} of the population, employ the β-coefficient loss formula to calculate the transmission loss P_L.

Step.4. Calculate the evaluation value (fitness) of each individual P_{Gi} in the population using the evaluation function given by (II.2) or (II.16).

Step.5. Compare each individual's evaluation value with it's Pg^{lbest} is the best fitness of the particle up and Pg^{gbest} is the best fitness among all candidates and find the center of mass P_{Gd}^{c} according to (IV.10).

Step.6. Calculate new candidates using eq.(IV.17)

$$P_{Gi,d}(k+1) = \alpha_1.P_{Gd}^{c}(k) + (1-\alpha_1).(\alpha_2.P_{Gd}^{lbest}(k) + (1-\alpha_2).P_{Gd}^{gbest}(k)) + \alpha_3.(P_{Gd,Max} - P_{Gd,Min}).rand/k \quad \text{(V.2)}$$

Where $i=1, 2, ..., n, d=1, 2, ..., m$

Where n is the population size, m is the number of units, $P_{Gd,Max}$ and $P_{Gd,Min}$ are parameter upper and lower limits, k number of iterations and α_1, α_2 and α_3 is the adjustable parameters.

Step.7. If the number of iterations reaches the maximum, then go to Step 8. Otherwise, go to Step 3.

Step.8. The individual that generates the latest Pg^{gbest} is the optimal generation power of each unit with the minimum total generation cost.

V.7.2. Simulation Results and Discussion :

The proposed HBB–BC algorithm has been applied to solve the ELD problem on three different test cases for verifying its feasibility. which are: a 6-generator system and a 15-generator system with quadratic cost function and transmission loss, a 40-generator system generators with valve-point loading effects, and a comparison with Big Bang–Big Crunch (BB–BC) method and other optimization methods.

In these examples, the software is implemented in MATLAB 2011Ra environment and run on a PC with Intel core i3 1.90. GHZ PC and 4 GB of RAM.

According to simulation, the following parameters in the HBB–BC algorithms methods are used:

-The number of generations is 100 and the population size is 100 individuals (candidates),

- The individual having minimum cost value is chosen for Big-Crunch phase,

- Take the adjustable parameters α_1=0.3, α_2 =0.5 and α_3 =1.3.

V.7.2.1. *Test System 1: Economic Dispatch of the six-unit system considering losses :*

In this case, to demonstrate the effectiveness of the proposed method, the HBB-BC are applied to solve the 6-unit power system, which considers the prohibited operating zones, ramp rate limits, and transmission network losses. The input data have been adopted from [156]. The load demand is 1263 MW. The simulation results are compared with BB-BC algorithm and various methods reported in literatures, such as the PSO [156], GA [156], CPSO [157], AIS [79], MTS [130] and BA [158] Their best solutions are shown in table V.25 and the performance parameters comparisons are shown in table V.26.

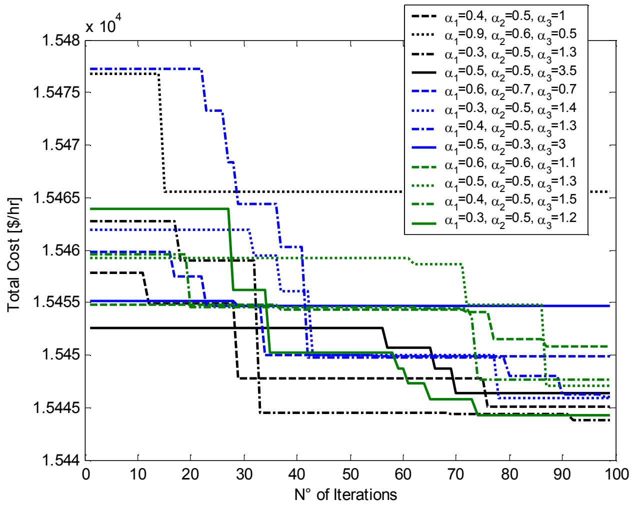


Figure V.34 : *The convergence characteristic of the six-generator systems for different adjustable parameters to the HBB–BC algorithms.*

Table V.25 : Comparison of the best results for a 6-unit system for demand of 1263 MW.

Generator Power Output	**HBB-BC**	**BB-BC**	**GA** [155]	**PSO** [156]	**CPSO** [157]	**AIS** [79]	**MTS** [130]	**BA** [158]
P_{g1} (MW)	441.36	455.48	474.81	447.50	434.43	458.29	449.37	438.65
P_{g2} (MW)	175.68	167.30	178.64	173.32	173.32	168.05	182.25	167.90
P_{g3} (MW)	262.82	271.76	262.21	263.47	274.47	262.52	254.29	262.82
P_{g4} (MW)	134.57	147.69	134.28	139.06	128.06	139.06	143.45	136.77
P_{g5} (MW)	169.98	163.49	151.90	165.48	179.48	178.39	161.97	171.76
P_{g6} (MW)	91.16	69.67	74.18	87.13	85.93	69.34	86.02	97.67
Power loss (MW)	12.57	12.41	13.02	12.96	12.69	12.65	14.35	12.57
Total Power(MW)	1275.57	1275.41	1276.02	1275.96	1275.69	1275.65	1277.35	1275.57
Total Cost ($/hr)	**15444.26**	15448.34	15459.0	15450.0	15446.0	15448.0	15451.6	15445.9

Fig. V.34 shows the convergence characteristic of the proposed method for six-generating unit system for different adjustable parameters. α_1, α_2 and α_3 are adjustable parameters controlling the influence of the global best and local best on the new position of the candidates, respectively.

Using α_1= 1.0 allows an initial search of the full range of values for each design variable. Fig. V.34 shows the effect of various values for α_1, α_2 and α_3 on the convergence characteristic of the proposed method for six-generating unit system. This figure shows that α_1=0.3, α_2=0.5 and α_3=1.3, are suitable values for HBB–BC algorithm. These parameter values are used for all other examples presented.

For this problem, can make the appropriate choice of the adjustable parameters codified somewhat, resulting from experimental and observational limits, where;

For the parameters α_1 its values are ranging between 0.5 and 0.1 for the role they play in a random distribution on the previous point.

And for the parameters α_2 it is better to be often 0.5 in order to guarantee the inclusion of best local and global fifty-fifty where both have an equal chance to influence,

And for α_3 are the largest in terms of field can be identified between 0.5 and 2, where there is no big difference with one of the values of the field, because it represent the size of the search space, and decreases with an increase the number of iterations. The best adjustable parameters are α_1=0.3, α_2=0.5 and α_3=1.3, it reaches to the optimum point after around 92 iterations.

Table V.26 : Performance parameters comparison case 1.

Methods	Cost ($/hr)			Average CPU time (s)	Standard deviation
	Min.	Average.	Max.		
GA [159]	15459.00	15469.00	15469.00	41.58	-
PSO [159]	15450.00	15454.00	15492.00	14.86	-
CPSO [157]	15446.00	15449.00	15490.00	8.13	-
AIS [79]	15448.00	15459.70	15472.00	NA	-
MTS [130]	15450.06	15451.17	15453.64	5.98	0.93
TSA [158]	15449.20	15495.82	15632.14	18.97	35.10
BA [158]	15445.87	15448.83	15452.92	5.64	1.56
BB-BC	15448.34	15495.16	15532.72	6.12	1.81
HBB-BC	**15444.26**	15446.46	15448.89	**5.6554**	**1.52**

The best results obtained from HBB-BC and other methods are compared in table V.25. The results show that the proposed approaches have high solution quality than others method as depicted.

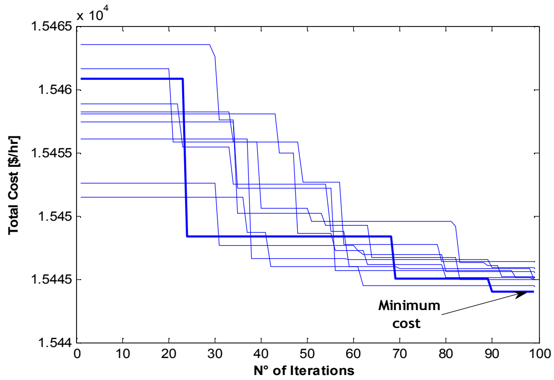


Figure V.35 : *Convergence characteristic of 6-generator system.*

Table V.26 shows the effectiveness in term of the solution quality among 100 trials of proposed methods. The solutions of the proposed methods higher quality than the rest methods in term of minimum cost, average cost, maximum cost, computational time and solution deviation. Fig. V.35 shows the convergence characteristic of the proposed combined methods.

V.7.2.2. *Test System 2: 15 units: Economic dispatch considering Transmission loss :*

The system contains 15 thermal units whose characteristics are taken from [131]. The load demand is 2630 MW. The loss coefficients β matrices are shown in Appendix. Transmission loss has been considered here. The result obtained from the proposed HBB-BC been compared with different PSO techniques [130], and different GA [130] methods and their best solutions are shown in table V.27 and the performance parameters comparisons are shown in table V.28. The convergence characteristic of the 15-generator systems in case of HBB-BC algorithm is shown in fig. V.36.

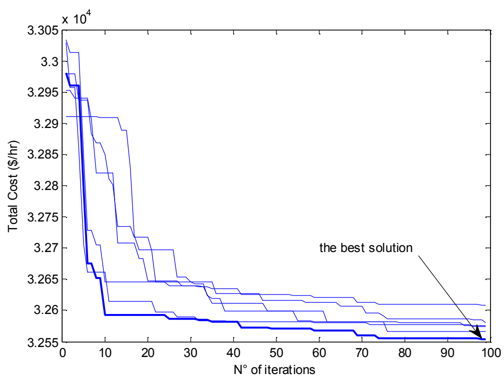


Figure V.36 : *Convergence characteristic of 15-generator system.*

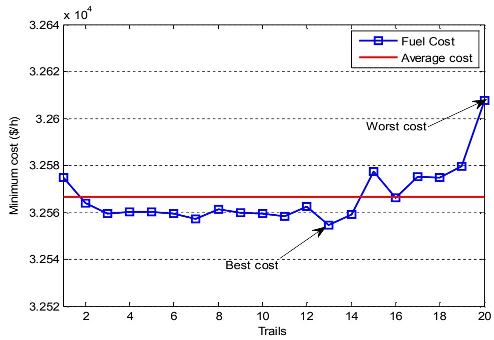


Figure V.37 : *Distribution of objective function value for 20 trails.*

The fig. V.37 shows distribution the generation cost of the best solution for each run in the test System 15 units.

Table V.28 : Comparison of HBB–BC performance with other methods.

Methods	Fuel Cost ($/hr.)				Average time (s)
	Best cost	Average cost	Worst cost	Standard deviation	
SA [130]	32786.40	32869.51	33028.95	112.32	71.25
GA [130]	32779.81	32841.21	33041.64	81.22	48.17
TSA [130]	32762.12	32822.84	32942.71	60.59	26.41
PSO [130]	32724.17	32807.45	32841.38	21.24	13.25
MTS [130]	32716.87	32767.21	32796.15	17.51	3.65
BB–BC	32659.35	32710.92	32750.92	18.23	13.14
HBB–BC	**32554.61**	32566.57	32607.71	12.29	12.65

Table V.27 : Best solution of 15 units system.

Unit power output	Methods						
	SA [130]	GA [130]	TS [130]	PSO [130]	MTS [130]	BB–BC	HBB–BC
P_1 (MW)	453.6646	445.5619	453.5374	454.7167	453.9922	454.9991	450.5573
P_2 (MW)	377.6091	380.0000	371.9761	376.2002	379.7434	455.0000	455.0000
P_3 (MW)	120.3744	129.0605	129.7823	129.5547	130.0000	130.0000	130.0000
P_4 (MW)	126.2668	129.5250	129.3411	129.7083	129.9232	130.0000	130.0000
P_5 (MW)	165.3048	169.9659	169.5950	169.4407	168.0877	227.1366	249.5857
P_6 (MW)	459.2455	458.7544	457.9928	458.8153	460.0000	460.0000	457.5472
P_7 (MW)	422.8619	417.9041	426.8879	427.5733	429.2253	465.0000	465.0000
P_8 (MW)	126.4025	97.8230	95.1680	67.2834	104.3097	60.0000	60.0000
P_9 (MW)	54.4742	54.2933	76.8439	75.2673	35.0358	25.0000	25.0000
P_{10} (MW)	149.0879	144.2214	133.5044	155.5899	155.8829	160.0000	42.0473
P_{11} (MW)	77.9594	77.3002	68.3087	79.9522	79.8994	20.0000	65.4235
P_{12} (MW)	73.9489	77.0371	79.6815	79.8947	79.9037	20.0000	72.3239
P_{13} (MW)	25.0022	31.1537	28.3082	25.2744	25.0220	25.0000	25.0000
P_{14} (MW)	16.0636	15.0233	17.7661	16.7318	15.2586	15.0000	15.0000
P_{15} (MW)	15.0196	33.6125	22.8446	15.1967	15.0796	15.0000	15.0000
Total output (MW)	2663.29	2661.23	2661.53	2661.19	2661.36	2662.13	2657.62
Power loss (MW)	33.2737	31.2363	31.4100	31.1697	31.3523	32.1358	27.4849
Total cost ($/h)	32786.40	32779.81	32762.12	32724.17	32716.87	32659.35	**32554.61**

V.7.2.3. *Test System 3: Large system: 40 units with valve-point loading effects :*

A system with 40 generators with valve point loading is used here. The input data are given in [135]. The load demand is 10500 MW.

Transmission loss has not been considered here. The result obtained from proposed HBB-BC method has been compared with NPSO-LRS [145], MDE [146], and other methods. Their best solutions are shown in table V.28 the performance parameters comparisons are shown in table V.29. The convergence characteristic of the 40-generator systems in case of HBB-BC algorithm is shown in fig. V.38.

Table V.28 : Best power output for 40-generator system (Load=10500 MW)

Generator Power Output	HBB-BC	BB-BC	NPSO_LRS [145]	NPSO [145]	MDE [146]	CBPSO-RVM [147]	FAPSO-NM [148]
P_{g1} (MW)	114.00	113.9987	113.9761	113.9891	110.831	114	111.38
P_{g2} (MW)	114.00	112.2160	113.9986	113.6334	110.815	114	110.93
P_{g3} (MW)	97.4243	97.4545	97.4241	97.55	97.399	97.4859	97.41
P_{g4} (MW)	179.7324	179.2473	179.7327	180.0059	179.734	179.7331	179.33
P_{g5} (MW)	88.6784	96.9995	89.6511	97	87.808	97	89.22
P_{g6} (MW)	140.00	140.0000	105.4044	140	140	140	140
P_{g7} (MW)	300.00	298.2952	259.7502	300	259.6	300	259.62
P_{g8} (MW)	284.5997	285.1021	288.4534	300	284.604	300	284.66
P_{g9} (MW)	284.5737	284.5527	284.646	284.5797	284.601	286.0079	284.66
P_{g10} (MW)	130.00	130.0000	204.812	130.0517	130	130	130
P_{g11} (MW)	94.00	94.000	168.8311	243.7131	168.799	94	168.82
P_{g12} (MW)	94.00	94.000	94	169.0104	168.799	94	168.82
P_{g13} (MW)	214.7623	214.7662	214.7663	125	214.759	214.7598	214.75
P_{g14} (MW)	304.5196	304.3154	394.2852	393.9662	394.28	304.5196	394.28
P_{g15} (MW)	394.2794	394.2604	304.5187	304.7586	394.28	394.2794	304.54
P_{g16} (MW)	394.2794	394.2604	394.2811	304.512	304.519	394.2794	394.3
P_{g17} (MW)	489.2795	489.2795	489.2807	489.6024	489.279	489.2794	489.29
P_{g18} (MW)	489.2795	489.2805	489.2832	489.6087	489.28	489.2794	489.29
P_{g19} (MW)	511.2845	511.3045	511.2845	511.7903	511.28	511.2794	511.28
P_{g20} (MW)	511.2845	511.3045	511.3049	511.2624	511.279	511.2794	511.29
P_{g21} (MW)	523.2196	523.2416	523.2916	523.3274	523.279	523.2796	523.33
P_{g22} (MW)	523.2196	523.2446	523.2853	523.2196	523.28	523.2794	523.48
P_{g23} (MW)	523.2196	523.2416	523.2797	523.4707	523.28	523.2797	523.33
P_{g24} (MW)	523.2196	523.2416	523.2994	523.0661	523.28	523.2802	523.33
P_{g25} (MW)	523.2196	523.2416	523.2865	523.3978	523.281	523.2795	523.33
P_{g26} (MW)	523.2196	523.2416	523.2936	523.2897	523.279	523.2794	523.33
P_{g27} (MW)	10.00	10.00	10	10.0208	10	10	10
P_{g28} (MW)	10.00	10.00	10.0001	10.0927	10	10	10
P_{g29} (MW)	10.00	10.00	10	10.0621	10	10	10
P_{g30} (MW)	89.3218	86.1458	89.0139	88.9456	92.645	97	88.7
P_{g31} (MW)	190.00	190.00	190	189.9951	190	190	190
P_{g32} (MW)	190.00	190.00	190	190	190	190	190
P_{g33} (MW)	190.00	190.00	190	190	189.999	190	190
P_{g34} (MW)	200.00	198.6117	199.9998	165.9825	164.831	200	165
P_{g35} (MW)	200.00	199.2348	165.1397	172.4153	164.802	166.8603	166
P_{g36} (MW)	200.00	199.9969	172.0275	191.2978	164.805	200	165
P_{g37} (MW)	110.00	110.00	110	109.9893	109.999	110	110
P_{g38} (MW)	110.00	110.00	110	109.9521	109.999	110	110
P_{g39} (MW)	110.00	110.00	93.0962	109.8733	109.999	110	110
P_{g40} (MW)	511.2845	511.2634	511.2996	511.5671	511.278	511.2794	511.3
Total Cost ($/hr)	**121471.72**	121523.57	121664.43	121704.73	121414.79	121555.32	121418.3

The proposed HBB-BC is efficiently and effectively implemented to solve the different economic load dispatch (ELD) problems, the HBB-BC optimization has several advantages over other evolutionary methods: Most significantly, a numerically simple algorithm and heuristic methods with relatively few control parameters; and the ability to solve problems that depend on large number of variables.

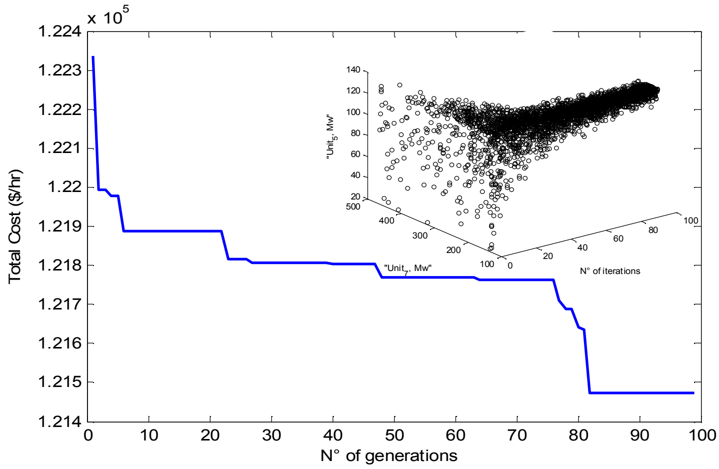


Figure V.38 : *Convergence characteristic of 40-generator system.*

Table V.29 : Comparison of results case 2 load=10500 MW.

Method	Minimum cost ($/h)	Mean cost ($/h)	Maximum cost ($/h)	Mean time (sec)
CEP [135]	123488.29	124793.5	126902.9	1956.9
FEP [135]	122679.71	124119.4	127245.6	1039.1
MFEP [135]	122647.57	123489.7	124356.5	2196.1
IFEP [135]	122624.35	123382.0	125740.6	1167.3
NPSO-LRS [145]	121664.43	122209.31	122981.59	19.8
MDE [146]	121414.79	121418.44	121466.04	-
GA [146]	121996.40	123807.97	122919.77	320.31
CBPSO-RVM[147]	121555.32	122281.14	123094.98	-
PS [136]	121415.14	122332.7	125486.3	42.98
FAPSO-NM [148]	121418.3	121418.80	121419.8	40
EP-SQP[134]	122323.97	122379.6	-	997.73
PSO [134]	123930.45	124155	-	933.39
PSO-SQP [134]	122094.67	122245.3	-	733.97
MPSO[149]	122252.27	-	-	-
ESO[138]	122122.16	122524.1	123143.1	-
DEC(2)-SQP(1) [138]	121741.98	122295.1	122839.3	14.26
TM [151]	122477.78	123078.2	124693.8	94.28
APSO [146]	121663.52	122153.67	122912.39	5.05
TS [153]	122288.38	122590.89	122424.81	238.35
ACO [153]	121811.37	121930.58	122048.06	92.54
BB-BC	121523.57	122026.09	122908.85	38.63
HBB-BC	**121471.72**	121984.24	122137.42	**16.52**

V.7.2.4. *Test System 4: IEEE 30 standard Environmental/economic power dispatch :*

The proposed algorithm is tested on standard IEEE 30-bus test for solving the CEED problem, the values of fuel cost, emission coefficients and The loss coefficients β matrices are given in appendix.5.

Table V.30 : Solutions of minimum fuel cost in IEEE 30 bus system (case 2).

Objectives	ED			
Method	MOPSO [159]	SPEA [160]	LP [161]	HBB-BC
Generation cost ($/h)	**608.10**	**607.807**	**606.314**	**605.624**
Emission (kg/h)	0.22276	0.22015	0.22330	0.2204
loss (MW)	3.05	3.38	2.60	2.42
P1	0.1689	0.1086	0.1500	0.1280
P2	0.2738	0.3056	0.3000	0.2931
P3	0.6026	0.5818	0.5500	0.5649
P4	0.9349	0.9846	1.0500	0.9945
P5	0.4923	0.5288	0.4600	0.5294
P6	0.392	0.3584	0.3500	0.3483
CPU time (s)	9.85	14.22	-	8.55

The result obtained from proposed method has been compared with other methods and their best solutions in tables V.30, V.31 and V.32. A convergence characteristic of the IEEE 30-bus test system in is shown in figs. V.39, V.40 and V.41.

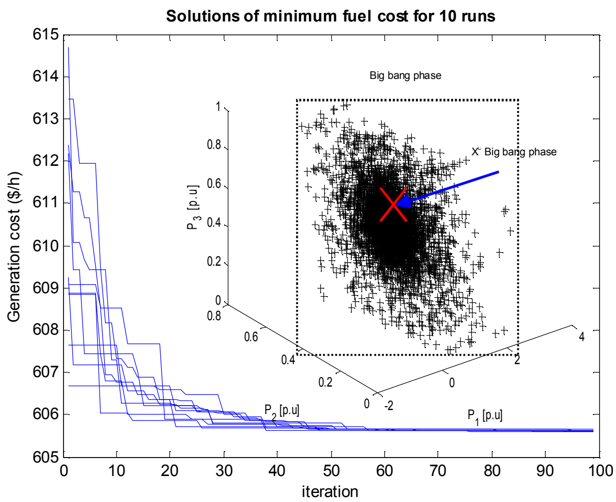


Figure V.39 : *Convergence characteristic of minimum fuel cost in IEEE 30 bus system for 10 run.*

Table V.31 : Solutions of minimum Emission in IEEE 30 bus system.

Objectives	EED			
Method	MOPS [159]	SPEA [160]	LP [161]	HBB-BC
Generation cost ($/h)	644.27	642.603	639.60	646.518
Emission (kg/h)	**0.19357**	**0.19422**	**0.1942**	**0.19419**
loss (MW)	3.05	3.05	1.60	3.54
P1	0.3832	0.4043	0.4000	0.4132
P2	0.5152	0.4525	0.4500	0.4595
P3	0.5616	0.5525	0.5500	0.5345
P4	0.3994	0.4079	0.4000	0.3879
P5	0.5248	0.5468	0.5500	0.5551
P6	0.4803	0.5005	0.5000	0.5191
CPU time (s)	9.85	14.22	-	08.25

CEED solution for the IEEE 30-bus test system is solved using HBB-BC algorithms. tables V.30, V.31 and V.32 summarize all the results for best fuel cost, best emission and combined economic and emission dispatch respectively. Convergence for best fuel cost, best emission and fuel cost and emission objective functions when optimized individually are shown in figs. V.39, V.40 and V.41 respectively.

From this tables, it can be deduced that the HBB-BC is equally capable of finding the best solution for each objective when two conflicting objectives are considered simultaneously.

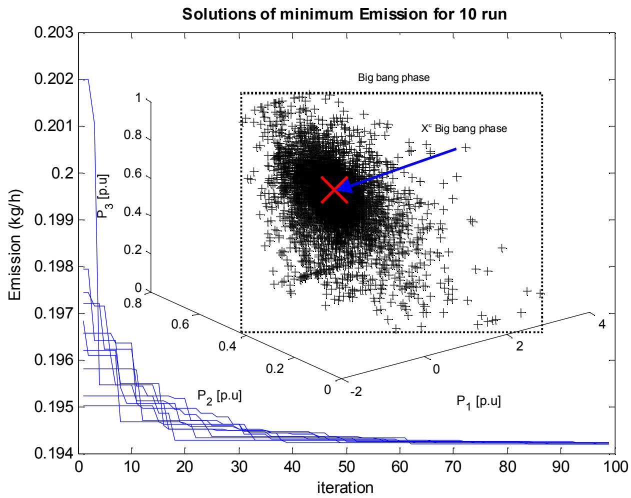


Figure V.40 : *Convergence characteristic of minimum Emission in IEEE 30 bus system for 10 run.*

Table V.32: Solutions combined economic and emission dispatch in IEEE 30 bus system.

Objectives	CEED			
Method	MOPS [159]	SPEA [160]	NSGA [161]	HBB-BC
Fuel cost ($/h)	614.81	616.069	617.80	623.763
Emission (kg/h)	0.20216	0.20118	0.2002	0.19705
Cost total ($/h)	**1221.29**	**1219.60**	**1218.40**	**1214.5**
loss (MW)	3.04	9.299	2.95	2.85
P1	0.2106	0.2594	0.2935	0.2998
P2	0.3854	0.3848	0.3645	0.4213
P3	0.5620	0.5645	0.5833	0.5480
P4	0.7260	0.7030	0.6763	0.5909
P5	0.5247	0.5431	0.5383	0.5393
P6	0.4558	0.4091	0.4076	0.4632
CPU time (s)	10.27	14.22	0.727	08.65

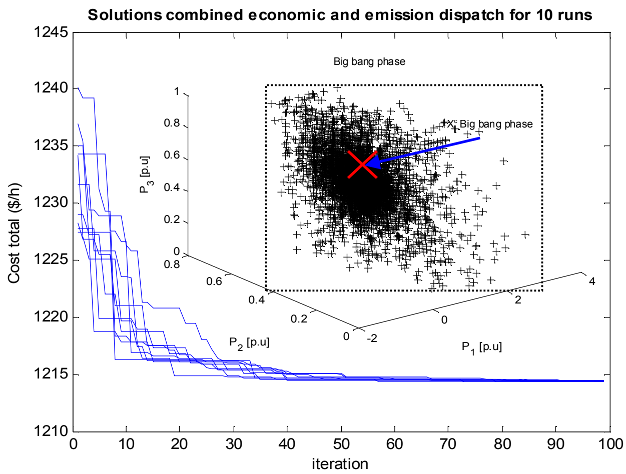


Figure V.41 : *Convergence characteristic of minimum Emission in IEEE 30 bus system for 10 run.*

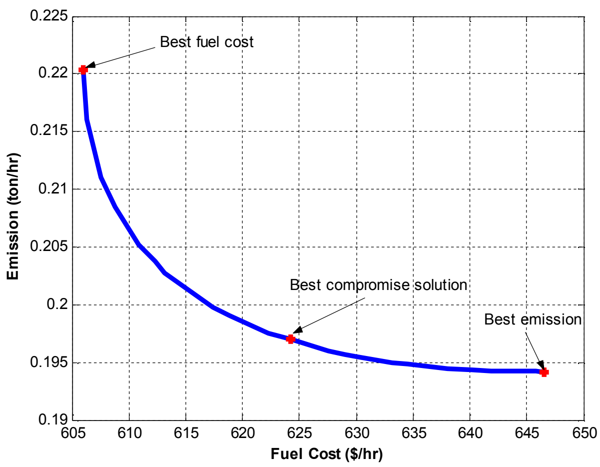


Figure V.43 : *Pareto-optimal front for fuel cost and emissions.*

Considering two objective functions: fuel cost and emission simultaneously, simulations results for the Pareto-optimal front were obtained as shown in the fig. V.43.

The comparisons of computational time of the methods in case combined economic and emission dispatch are shown in table V.32. Clearly, the computational time of the NSGA algorithm method is lowest in comparison followed in the second rank HBB-BC to those of the other methods.

The comparison of numerical results of combined economic and emission dispatch problem (CEED) using the HBB-BC method with the results obtained by other heuristic approaches are performed to demonstrate the robustness of the present algorithm.

The results show that the optimal dispatch solutions determined by HBB-BC lead to lower active power loss then that found by other heuristic methods, which confirms that the HBB-BC is well capable of determining the global or near global optimum dispatch solution.

V.8. Conclusion :

In this chapter, a different metaheuristics algorithms (GA, PSO, PS, BB–BC, ABC) were implemented for solving different types of the economic dispatch problems, also we propose a new hybrid algorithm (GA–PS, PSO–PS, HBB–BC) for solving the EDP, the proposed methods are tested and validated on various electrical test systems and cases taking into different constraints, the results show that the optimal dispatch solutions determined, which confirms that the different algorithms are well capable of determining the global or near global optimum dispatch solution. The comparison of numerical results with those that reported in the literature recently is performed to demonstrate the robustness of the proposed techniques and confirmed its potential for solving practical economic dispatch problems.

The comparative study between the solvers is carried out in terms of absolute cost, computational complexity, and fitness value achieved by the GA, PSO, PS, BB-BC, ABC, GA-PS, PSO-PS and HBB-BC algorithms, the hybrid algorithms are found to be better than that of global and local search techniques applied independently for all variants of EDPs.

CHAPTER VI

Thermal Unit Commitment solution applying Genetic Algorithms (GAs)

VI.1. Introduction :

In this chapter, a genetic algorithm (GA) is proposed to solve thermal unit commitment (UC) problem. The objective of UC is to determine the optimal generation of the committed units to meet the load demand and spinning reserve at each time interval, such that the overall cost of generation is minimized, while satisfying different operational constraints.

Also, we applied a crossover operator ring crossover for genetic algorithm (RCGA) to solve the unit commitment (UC) problem, UC is the process of determining which generators should be operated each day to meet the daily demand of the system. Economic dispatch and unit commitment are widely used for the real time operation of power system. Many constraints can be placed on the unit commitment problem such as spinning reserve constraint, thermal unit constraint and other constraints. The results obtained show that, with the application of the proposed method (RCGA) to the unit commitment problem, better convergences and solutions are obtained than with the application of conventional genetic algorithm.

VI.2. A genetic algorithm to solve thermal UC problem :

The optimum economic operation and planning of electric power generation systems is an important issue in electric power industry. Unit commitment (UC) [162] plays a vital role in generation resource management. It is an optimization problem of determining the schedule of generating units within a power system in or-der to minimize fuel cost while satisfying a number of constraints such as unit capacity limit, ramp rate limits, spinning reserve constraints, minimum up time and down time constraints. However, UC problem not only minimizes the fuel cost (production costs) but also minimize the transition costs (start-up/shut-down costs). The spinning reserve constraint used in UC, describes the reliability requirement by taking the generator outages into consideration [163].

Well known traditional techniques such as integer programming (IP) [31, 164], dynamic programming (DP) [165–166], branch and bound [167], Bender's decomposition [168], and Lagrangian relaxation (LR) [169, 170] have been used to solve the UCP. More recently, metaheuristic approaches have been used such as simulated annealing (SA) [171], tabu search [172], and genetic algorithms (GA) [58, 173]. Other problem-specific heuristics can be found in [174–176].

Genetic algorithms (GAs) represent general-purpose search and optimization technique based on evolutionary ideas of natural selection and genetics [177]. They simulate natural processes based on principles of Lamarck and Darwin. In 1975, Holland developed this idea in his book "Adaptation in natural and artificial systems". He described how to apply the principles of natural evolution to optimization problems and built the first GAs. Holland's theory has been further developed and now GAs standup as a powerful tool for solving search and optimization problems. GAs are based on the principle of genetics and evolution [178]. Today, there exists many variations on GAs and term "genetic algorithm" is used to describe concepts sometimes very far from Holland's original idea [179]. The two most commonly employed genetic search operators are crossover and mutation. Crossover produces offspring by recombining the information from two parents [177]. Mutation prevents convergence of the population by flipping a small number of randomly selected bits to continuously introduce variation. The driving force behind GAs is the unique cooperation between selection, crossover and mutation operator. A genetic operator is a process used in GAs to maintain genetic diversity. The most widely used genetic operators are recombination, crossover and mutation [177].

The main goal of this section is to use the GA algorithm to solve the unit-scheduling problem, and the Lambda-iteration method is used to solve the economic dispatch problem. Two systems are presented to investigate the efficiency of the proposed method. With the proposed method, the total generation cost can be remarkably reduced while considering various constraints reflecting the practical system.

VI.2.1. A GA to solve the UC problem :

GA for the solution of UC problem have been earlier proposed by various researchers [58, 173], most of them differing in the method of representation, decoding and evaluation. However, earlier approaches do not provide sufficient or any information regarding the handling of constraints and other objectives. Since a UC problem is incomplete without the consideration of the minimum up time (MUT) and minimum down time (MDT) constraints, a detailed methodology for obtaining the complete solution with constraints is described in this paper [59].

To resolve the UCP using the GA method proposed, the implementation consists of initialization, cost calculations, elitism, reproduction, crossover, mutation, economic dispatch (ED) calculations, swap mutation operator and repair operator of the UC schedules. A flowchart of the algorithm is given in fig. VI.1 [57].

A member of the population consists of a matrix with dimension equal to the number of generators by the number of scheduling periods. This matrix represents the on/off status of the generating units. The first step of initialization consist of finding the cheapest economic dispatches for each hour that meet system demand and a 10% spinning reserve. A member of the population is then created by randomly choosing one of the cheapest economic dispatches for each hour [57].

Different steps of UC based GA algorithm is mentioned below:

VI.2.1.*1 Initial Population* :

A number of NP initial binary-coded solutions (genotype) are produced at random to form the initial population. Each population is evaluated, and its fitness value is calculated from equation (III.3). With the initial population produced and evaluated, genetic evolution takes place by means of three genetic operators namely Selection, Crossover and Mutation.

VI.2.1.*2. Roulette wheel parent selection :*

After the evolution of the initial randomly generated population the GA begins the creation of the new generation of solutions. Two genotypes are selected from parent genotypes with a probability proportional to the genotypes relative fitness within the population [180].

VI.2.1.3. *Crossover :*

To get the new patterns of genetic strings during the evolution process, crossover operator: ring crossover is used.

VI.2.1.4. *Mutation :*

With a small probability, randomly chosen bits of the offspring genotypes change from ‘0’ to ‘1’ and vice versa [180].

VI.2.1.5. *Selection :*

The entire population, including parent and offspring are arranged in descending order. The first NP solutions survive and are transcribed along with their elements to form the basis of the next generation.

The above process is repeated until the given maximum generation count is reached.

In addition, some advanced GA features are also implemented including Elitism, Turn-off generator mutation, Swap mutation operator and Repair operator [180].

VI.2.1.6. *Elitism :*

The best solution of every generation is copied to the next so that the possibility of its destruction through a genetic operator is eliminated.

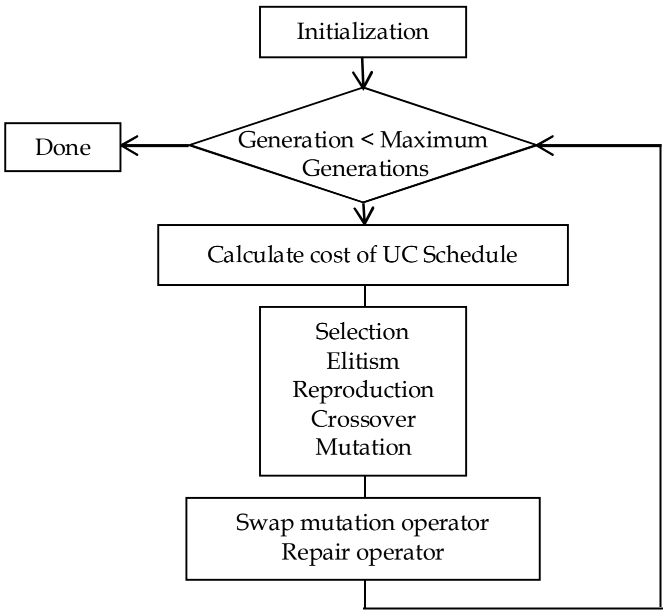


Figure VI.1 : *GA flowchart.*

VI.2.1.7. *Swap mutation operator :*

Based upon the full load average production cost of the units bits where exchanged for each scheduled of a genotype with some probability to avoid the local convergence [58].

VI.2.1.8. *Repair operator :*

All the individuals of the new population are subjected to a mechanism intended to repair violations of the constraints of minimum start-up and shut-down times. This process is only carried out in one randomly selected generating unit [181].

VI.2. Experimental results :

In this section, the GA is applied to solve UC problems. For implementing GA technique to solve UC problem, population size of 40 and the maximum number of generation (iterations) of 300 are taken. Software is developed in MATLAB to solve seven different UC problems and tested on a Pentium IV, 3-GHz personal computer with 4 GB RAM. The algorithm is tested in two systems (Small-scale and Large-scale UC problem) and the results of the proposed method is compared to another GA methods GA [182], GA [60], GA [59], SGA [180], TLGA [180], FPGA [183], GA [58] and ICGA [184], and compared with other metaheuristic methods BPSO [60], GA [60], APSO [185], BP [186], TSGB [186], IPSO [187], and Hybrid PSO-SQP [87]

In all experiments, parameters of GA for experiments were as following: Gaussian mutation with P_m mutation coefficient of 0.2 and crossover rate P_c of 0.9 was used, initial population NP of size 40 was randomly created and used in experiments.

VI.2.1. *Small-scale UC problem (ten-unit) :*

In this case, 10 units system has been tested in order to prove the applicability of the proposed method for solving the UC problem. The fuel cost data along with generation constraints of 10 units system and Power demands for 24 h are taken from [60] and also given in Appendix. 6 (A .11 and A.12, respectively). In the simulation, the reserve is required to be 5% and 10% of the power demand. The proposed GA approach is applied to solve the UC problem considering all constraints such as generator constraints, reserve constraint and minimum up time and minimum down time. Scheduling of the generation obtained by the proposed GA method for 10 units system is given in table VI.1 for case with 5% of spinning reserve and in table VI.2 for case with 10% of spinning reserve. To show the advantages of the proposed method, we will compare the performance of the proposal method with other met-heuristic methods in table VI.3 and table VI.4, also shows that the average and worst cost produced by GA is least compared to other methods emphasizing its superiority in terms of robustness; results of table VI.4 also shows that proposed GA method takes acceptable average computational time (CT) than other algorithms. Figs. VI.2 and VI.3 shows the convergence tendency of the best evaluation value in the population during GA processing for 10 unit system with different spinning reserve.

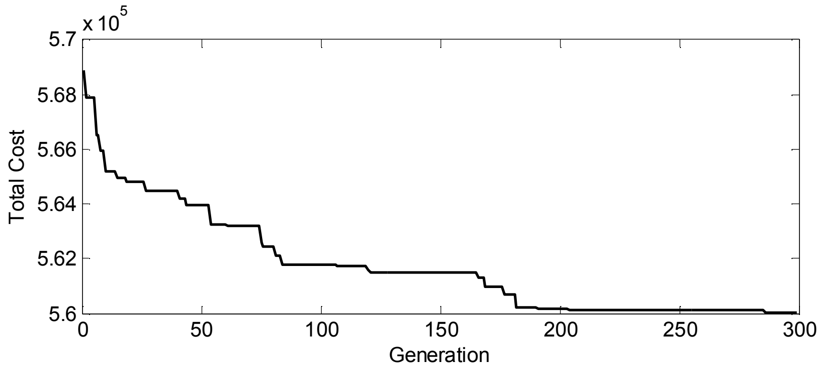


Figure VI.2 : *Typical performance of the GA in case with 5% of spinning reserve.*

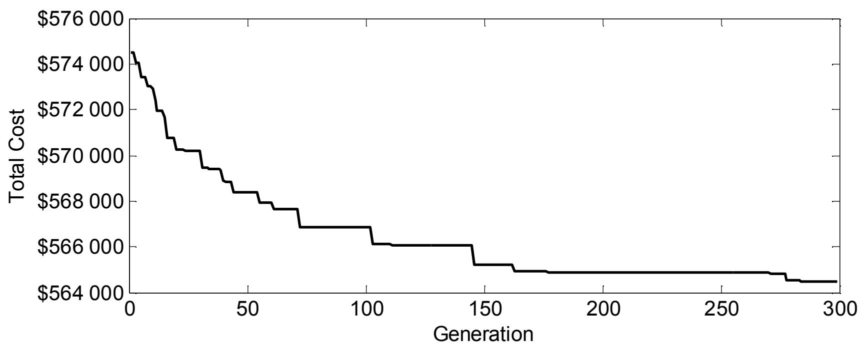


Figure VI.3 : *Typical performance of the GA in case with 10% of spinning reserve.*

Table VI.3 : Simulation results of 10 unit system with 5% of spinning reserve.

Methods	Best ($)	Average ($)	Worst ($)
BPSO [60]	565,804	566,992	567,251
GA [60]	570,781	574,280	576,791
APSO [185]	561,586	–	–
BP [186]	565,450	–	–
TSGB [186]	560,263.92	–	–
IPSO [187]	558,114.80	–	–
Hybrid PSO-SQP [87]	568,032.30	–	–
GA	560,013.87	563,302.10	565,933.22

Sign (–) means that no amount has been reported.

Table VI.1 : Best individual-Generation schedule and costs obtained by GA for 10 unit system with 5% of spinning reserve.

Hou r	Unit Schedule	Production Cost ($)	Transiti on Cost ($)	Spinning Reserve [MW]	Generation schedule (MW)									
					Unit 1	Unit 2	Unit 3	Unit 4	Unit 5	Unit 6	Unit 7	Unit 8	Unit 9	Unit 10
1	1100000000	13683.12	0	210	455	245	0	0	0	0	0	0	0	0
2	1100000000	14554.49	0	160	455	295	0	0	0	0	0	0	0	0
3	1100100000	16809.44	900	222	455	370	0	0	25	0	0	0	0	0
4	1100100000	18597.66	0	122	455	455	0	0	40	0	0	0	0	0
5	1100100000	19608.53	0	72	455	455	0	0	90	0	0	0	0	0
6	1101100000	21860.28	1120	102	455	455	0	130	60	0	0	0	0	0
7	1101101000	23541.20	520	137	455	455	0	130	85	0	25	0	0	0
8	1101101000	24569.98	0	87	455	455	0	130	135	0	25	0	0	0
9	1111101000	26842.13	1100	117	455	455	130	130	105	0	25	0	0	0
10	1111101100	29807.79	60	72	455	455	130	130	162	0	25	43	0	0
11	1111111001	31253.39	400	102	455	455	130	130	162	80	28	0	0	10
12	1111111011	33286.59	60	107	455	455	130	130	162	80	25	0	53	10
13	1111111000	30057.55	60	152	455	455	130	130	162	33	25	10	0	0
14	1111110000	26588.96	0	112	455	455	130	130	110	20	0	0	0	0
15	1101110000	24318.01	0	82	455	455	0	130	140	20	0	0	0	0
16	1101100000	20895.88	0	152	455	440	0	130	25	0	0	0	0	0
17	1101100000	20020.01	0	202	455	390	0	130	25	0	0	0	0	0
18	1101100000	21860.28	0	102	455	455	0	130	60	0	0	0	0	0
19	1101110000	24318.01	170	82	455	455	0	130	140	20	0	0	0	0
20	1111110110	30164.02	670	122	455	455	130	130	162	48	0	10	10	0
21	1111110000	26588.96	0	112	455	455	130	130	110	20	0	0	0	0
22	1111000000	21879.33	0	70	455	385	130	130	0	0	0	0	0	0
23	1110000000	17795.28	0	140	455	315	130	0	0	0	0	0	0	0
24	1110000000	16052.85	0	240	455	215	130	0	0	0	0	0	0	0
Total		**554,953.87**	**5060**	**3078**	Total generation cost ($):					**560,013.8727**				

Table VI.2 : Best individual-Generation schedule and costs obtained by GA for 10 unit system with 10% of spinning reserve

Hour	Unit Schedule	Production Cost ($)	Transition Cost ($)	Spinning Reserve [MW]	Generation schedule (MW)									
					Unit 1	Unit 2	Unit 3	Unit 4	Unit 5	Unit 6	Unit 7	Unit 8	Unit 9	Unit 10
1	1100000000	13683.12	0	210	455	245	0	0	0	0	0	0	0	0
2	1100000000	14554.49	0	160	455	295	0	0	0	0	0	0	0	0
3	1100100000	16809.44	900	222	455	370	0	0	25	0	0	0	0	0
4	1100100000	18597.66	0	122	455	455	0	0	40	0	0	0	0	0
5	1101100000	20020.01	560	202	455	390	0	130	25	0	0	0	0	0
6	1111100000	22387.04	1100	232	455	360	130	130	25	0	0	0	0	0
7	1111100000	23261.97	0	182	455	410	130	130	25	0	0	0	0	0
8	1111100000	24150.34	0	132	455	455	130	130	30	0	0	0	0	0
9	1111110001	27331.67	400	167	455	455	130	130	100	20	0	0	0	10
10	1111111001	30086.01	520	152	455	455	130	130	162	33	25	0	0	10
11	1111111011	31944.52	60	157	455	455	130	130	162	73	25	0	10	10
12	1111111111	33890.16	60	162	455	455	130	130	162	80	25	43	10	10
13	1111111001	30086.01	0	152	455	455	130	130	162	33	25	0	0	10
14	1111110100	27303.21	30	167	455	455	130	130	100	20	0	10	0	0
15	1111100000	24150.34	0	132	455	455	130	130	30	0	0	0	0	0
16	1111100000	21513.65	0	282	455	310	130	130	25	0	0	0	0	0
17	1111100000	20641.82	0	332	455	260	130	130	25	0	0	0	0	0
18	1111100000	22387.04	0	232	455	360	130	130	25	0	0	0	0	0
19	1111100000	24150.34	0	132	455	455	130	130	30	0	0	0	0	0
20	1111110111	30883.37	350	177	455	455	130	130	162	38	0	10	10	10
21	1111110010	27321.52	0	167	455	455	130	130	100	20	0	0	10	0
22	1101110000	22276.37	0	182	455	455	0	130	40	20	0	0	0	0
23	1100010000	17645.36	0	90	455	425	0	0	0	20	0	0	0	0
24	1100000000	15427.41	0	110	455	345	0	0	0	0	0	0	0	0
Total		**560,503.01**	**3980**	**4255**	Total generation cost ($):					**563,478.541239**				

Table VI.4 : Comparison of solution quality with other GA methods with 10% of spinning reserve.

Methods	Best generation cost ($)	Average generation cost ($)	Worst generation cost ($)	Standard deviation (%)	The computation time (sec.)
GA [182]	565,866	567,329	571,336	0.26 (%)	113
GA [60]	570,781	574,280	576,791	1549.9 ($)	62.29
GA [59]	609,023.69	–	–	–	73.68
SGA [180]	565,121	–	622,846	9.27 (%)	462.31
TLGA [180]	56,4426	–	566,182	0.31 (%)	439.313
FPGA [183]	564,094	566,675	569,237	0.33 (%)	–
GA [58]	565,825	–	–	–	–
ICGA [184]	566,404	–	–	–	–
GA	564,483.01	567,136.23	569,5750.11	0.42 (%)	112.52

VI.2.2. *Large-scale UC problem (20 units) :*

To verify the effectiveness and efficiency of the proposed GA method in solving large-scale UC problem, the proposed method is applied on 20 unit systems. For 20 units, the initial 10 units are duplicated and the demand is multiplied by 2. The statistical results obtained by different algorithms of 20 units test system are shown in table VI.5.

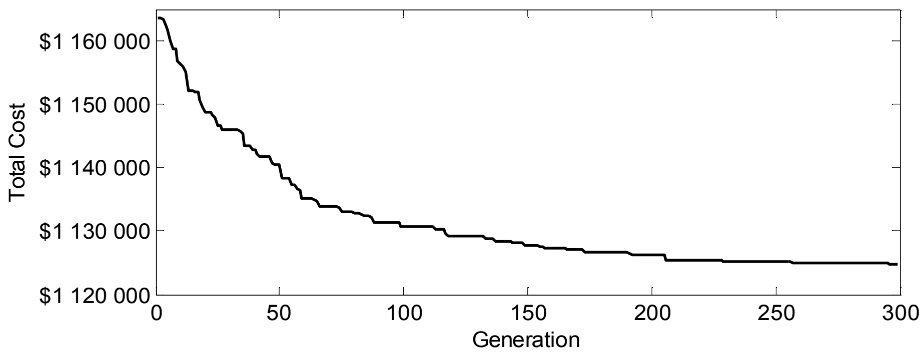


Figure VI.4 : *Convergence characteristic of fuel cost using GA for 20-units based UC problem.*

From the simulation results, it is very evident that GA not only has found the highest quality results among the all algorithms compared. The best UC schedule of the 20-unit test system on 24-h scheduling horizon with one-hour interval are shown in table VI.6. To illustrate the convergence property of the proposed algorithm, fuel cost values over 300 iterations for 20 units systems are plotted in fig. VI.4.

Table VI.5 : Simulation results of 20-unit system with 10% of spinning reserve.

Methods	Best generation cost ($)	Average generation cost ($)	Worst generation cost ($)
ICGA [184]	–	1,127,244	–
LRGA [188]	–	1,122,622	–
GA [58]	1,126,243	–	1,132,059
LR [58]	1,130,660	–	–
EP [189]	1,125,494	1,127,257	1,129,793
AG [190]	–	1,124,651	–
BCGA [184]	1,130,291	–	–
UCC-GA [191]	1,125,516	–	–
DPLR [60]	1,128,098	–	–
SF [192]	1,125,161	–	–
EALR [60]	1,123,297	–	–
CR-GA [193]	–	1,236,981	–
Proposed	1,126,185	1,127,268	1,1307,64

Table VI.6 : Best UC schedule of the 20-unit test system on 24 h scheduling horizon with 1 hour interval

Hour	Generating Unit																			
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	**455**	**245**	0	0	0	0	0	0	0	0	**455**	**245**	0	0	0	0	0	0	0	0
2	**445**	**295**	0	0	0	0	0	0	0	0	**445**	**295**	0	0	0	0	0	0	0	0
3	**445**	**382.5**	0	0	**25**	0	0	0	0	0	**445**	**382.5**	0	0	0	0	0	0	0	0
4	**445**	**417.5**	**130**	0	**25**	0	0	0	0	0	**445**	**417.5**	0	0	0	0	0	0	0	0
5	**445**	**402.5**	**130**	**130**	**25**	0	0	0	0	0	**445**	**402.5**	0	0	0	0	0	0	0	0
6	**445**	**427.5**	**130**	**130**	**25**	0	0	0	0	0	**445**	**427.5**	0	**130**	0	**20**	0	0	0	0
7	**445**	**455**	**130**	**130**	**35**	0	0	0	0	0	**445**	**455**	0	**130**	**35**	**20**	0	0	0	0
8	**445**	**450**	**130**	**130**	**25**	0	0	0	0	0	**445**	**449.5**	**130**	**130**	**25**	**20**	0	0	0	0
9	**445**	**455**	**130**	**130**	**95**	0	**25**	0	0	0	**445**	**455**	**130**	**130**	**95**	**20**	**25**	0	0	0
10	**445**	**455**	**130**	**130**	**162**	**33**	**25**	**10**	0	**10**	**445**	**455**	**130**	**130**	**162**	**33**	**25**	0	0	0
11	**445**	**455**	**130**	**130**	**162**	**73**	**25**	**10**	**10**	**10**	**445**	**455**	**130**	**130**	**162**	**73**	**25**	**10**	0	0
12	**445**	**455**	**130**	**130**	**162**	**80**	**25**	**43**	**10**	**10**	**445**	**455**	**130**	**130**	**162**	**80**	**25**	**43**	**10**	**10**
13	**445**	**455**	**130**	**130**	**162**	**33**	**25**	0	0	**10**	**445**	**455**	**130**	**130**	**162**	**33**	**25**	0	**10**	0
14	**445**	**455**	**130**	**130**	**100**	0	**25**	**10**	0	0	**445**	**455**	**130**	**130**	**100**	0	**25**	0	0	0
15	**445**	**455**	**130**	**130**	**30**	0	0	0	0	0	**445**	**455**	**130**	**130**	**30**	0	0	0	0	0
16	**445**	**310**	**130**	**130**	**25**	0	0	0	0	0	**445**	**310**	**130**	**130**	**25**	0	0	0	0	0
17	**445**	**260**	**130**	**130**	**25**	0	0	0	0	0	**445**	**260**	**130**	**130**	**25**	0	0	0	0	0
18	**445**	**360**	**130**	**130**	**25**	0	0	0	0	0	**445**	**360**	**130**	**130**	**25**	0	0	0	0	0
19	**445**	**455**	**130**	**130**	**30**	0	0	0	0	0	**445**	**455**	**130**	**130**	**30**	0	0	0	0	0
20	**445**	**455**	**130**	**130**	**162**	**43**	0	**10**	**10**	0	**445**	**455**	**130**	**130**	**162**	**43**	0	**10**	**10**	**10**
21	**445**	**455**	**130**	**130**	**105**	**20**	0	0	**10**	0	**445**	**455**	**130**	**130**	**105**	**20**	0	**0**	0	**0**
22	**445**	**417.5**	**130**	**130**	**25**	**20**	0	0	0	0	**445**	**417.5**	**130**	0	0	**20**	0	**0**	0	**0**
23	**445**	**432.5**	0	0	**25**	0	0	0	0	0	**445**	**432.5**	0	0	0	**0**	0	**0**	0	**0**
24	**445**	**345**	0	0	**0**	0	0	0	0	0	**445**	**345**	0	0	0	**0**	0	**0**	0	**0**

This section presents a genetic algorithm for solving the thermal unit commitment (UC) problem. The proposed algorithm is applied on two test systems using 10 and 20 thermal units in a scheduling period of 24 hours with different types of constraints and load profile in specific scheduling period. The test results demonstrate the effectiveness of the GA in searching global or near global optimal solution to the UC problem. Also the results show a good convergence and higher precision.

A disadvantage of the GAs is that, since they are stochastic optimization algorithms, the optimality of the solution they provide cannot be guaranteed, another disadvantage of GA-UC algorithms is their high execution time.

VI.3. Optimal UC using Genetic Algorithm based Ring Crossover :

The main goal of this section is to use the RCGA algorithm to solve the unit-scheduling problem, and the Lambda-iteration method is used to solve the economic dispatch problem. A matrix representation of the chromosome representing each scheduled unit's status during all scheduling period is adopted. The calculation processes of the RCGA algorithm involved in solving the UC problem are explained in detail.

VI.3.1. The Proposed Method :

VI.3.1.1. *Overview of genetic algorithms :*

Genetic Algorithms are inspired by the study of genetics. They are conceptually based on naturally evolution mechanisms working on populations of solutions in contrast to other search techniques that work on a single solution [194]. The algorithm starts with the creation of a combination of coded structures called Chromosomes (solutions) which make up the initial population. The criterion which evaluates the quality of each Chromosome, is given by the Fitness corresponding to the evaluation of each individual for the objective function. Once the fitness of each of the individuals in the population is known, it is subjected to a Selection process in which the best evaluated individuals have a greater probability of being chosen as Parents for the exchange of genetic information called Crossover. Then a percentage of the Offspring's (individuals generated in the crossover) are subjected to the Mutation process in which a random change is generated in the chromosome. This mutation process provides greater diversity between the individuals in the population. When the crossover and mutation processes are complete a new population is generated which replaces the original population. This must be repeated until one of the convergence criteria defined for the problem is met. Each of these cycles is known as a Generation [181].

VI.3.1.2. *Crossover operators :*

The crossover operator is a genetic operator that combines two chromosomes (parents) to produce a new chromosome (offspring). The idea behind crossover is that the new chromosome may be better than both of the parents if it takes the best characteristics from each of the parents [195].

VI.3.1.3. *Single Point Crossover :*

When performing crossover, both parental chromosomes are split at a randomly determined crossover point. Subsequently, a new child genotype is created by appending the first part of the first parent with the second part of the second parent [196–197]. A single crossover point on both parents' organism strings is selected. All data beyond that point in either organism string is swapped between the two parent organisms. Fig. VI.5 shows the single point crossover (SPC) process [177].

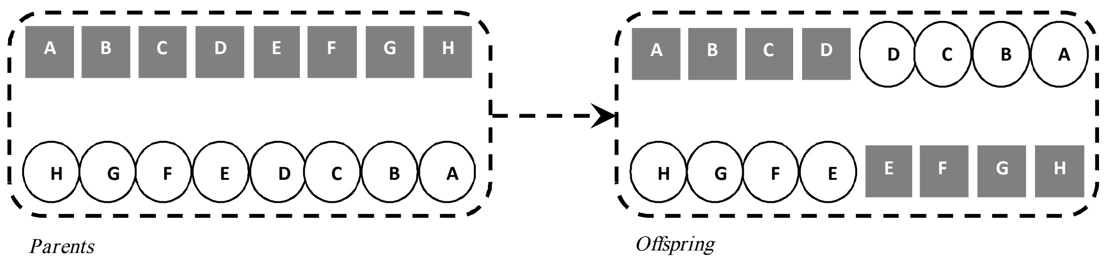


Figure VI.5 : *Single point crossover.*

VI.3.1.4. *Two Point Crossover :*

Apart from SPC, many different crossover algorithms have been devised, often involving more than one cut point. It should be noted that adding further crossover points reduces the performance of the GA. The problem with adding additional crossover points is that building blocks are more likely to be disrupted. However, an advantage of having more crossover points is that the problem space may be searched more thoroughly. In two-point crossover (TPC), two crossover points are chosen and the contents between these points are exchanged between two mated parents [198–199].

In fig. VI.6, the arrows indicate the crossover points. Thus, the contents between these points are exchanged between the parents to produce new children for mating in the next generation.

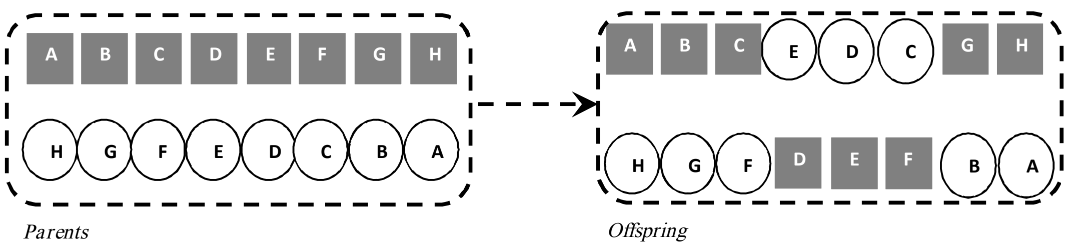


Figure VI.6 : *Two point crossover.*

VI.3.1.5. *Crossover Operator: Ring Crossover :*

Y. Kaya, M. Uyar and R. Tekin in their paper [177] have shown a new method of crossover that operates on a circular method. The experimental results did show that a good diversity was preserved because of the operator and the performance of this algorithm was much better than other operators.

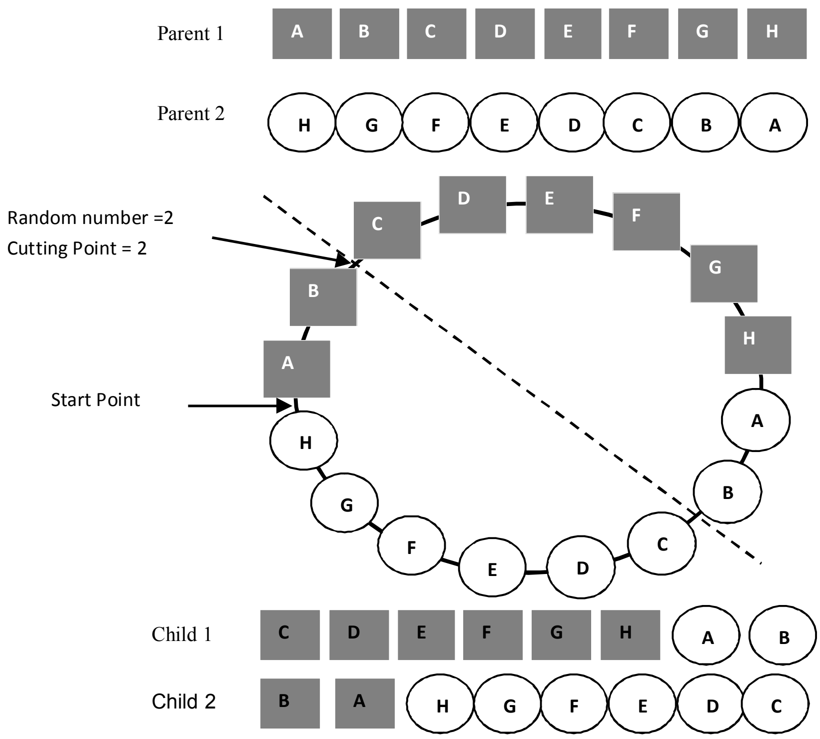


Figure VI.7 : *Ring crossover.*

The steps of the Ring Crossover operator are shown in fig. VI.7, this is the crossover operator (RC) that will be used for our problem UC.

VI.3.2. Unit Commitment Using RCGA Method :

GA for the solution of UC problem have been earlier proposed by various researchers [58], [200], most of them differing in the method of representation, decoding and evaluation. However, earlier approaches do not provide sufficient or any information regarding the handling of constraints and other objectives. Since a UC problem is incomplete without the consideration of the minimum up time (MUT) and minimum down time (MDT) constraints, a detailed methodology for obtaining the complete solution with constraints is described in this paper [201].

To resolve the UCP using the RCGA method proposed, the solution may be represented, as shown in fig. VI.8, as a matrix of states of order NxH where N is the total number of generating units and H is the total number of hours in the study period. A binary code is used in which 1 represents state of the unit as On and 0 represents the state of the unit as Off.

unit \ *hour*	1	2	3	4	…	23	24
1	1	1	1	1	…	1	0
2	1	0	1	1	…	0	1
3	0	0	1	0	…	0	0
⋮	⋮	⋮	⋮	⋮		⋮	⋮
	1	1	0	1	…	1	0
N	0	0	0	0	…	0	0

Figure VI.8 : *Solution representation.*

In this section the proposed algorithm is applied to solve the UC problem. To apply the RCGA, the following steps have to be taken [180].

Step 1: Initial Population: A number of NP initial binary-coded solutions (genotype) are produced at random to form the initial population. Each population is evaluated, and its fitness value is calculated from equation (III.3). With the initial population produced and evaluated, genetic evolution takes place by means of three genetic operators namely Selection, Crossover and Mutation.

Step 2: Roulette wheel parent selection: After the evolution of the initial randomly generated population the GA begins the creation of the new generation of solutions. Two genotypes are selected from parent genotypes with a probability proportional to the genotypes relative fitness within the population.

Step 3: Crossover: To get the new patterns of genetic strings during the evolution process, crossover operator: ring crossover is used.

Step 4: Mutation: With a small probability, randomly chosen bits of the offspring genotypes change from ‘0’ to ‘1’ and vice versa.

Step 5: Selection: The entire population, including parent and offspring are arranged in descending order. The first NP solutions survive and are transcribed along with their elements to form the basis of the next generation.

Step 6: Elitism: The best solution of every generation is copied to the next so that the possibility of its destruction through a genetic operator is eliminated.

Step 7: Turn-off generator mutation: This mutation operator turns off a generator for the scheduling period. The operator to be turned off was randomly determined. This operator is performed with some probability [57].

Step 8: Repair operator: All the individuals of the new population are subjected to a mechanism intended to repair violations of the constraints of minimum start-up and shut-down times. This process is only carried out in one randomly selected generating unit [181].

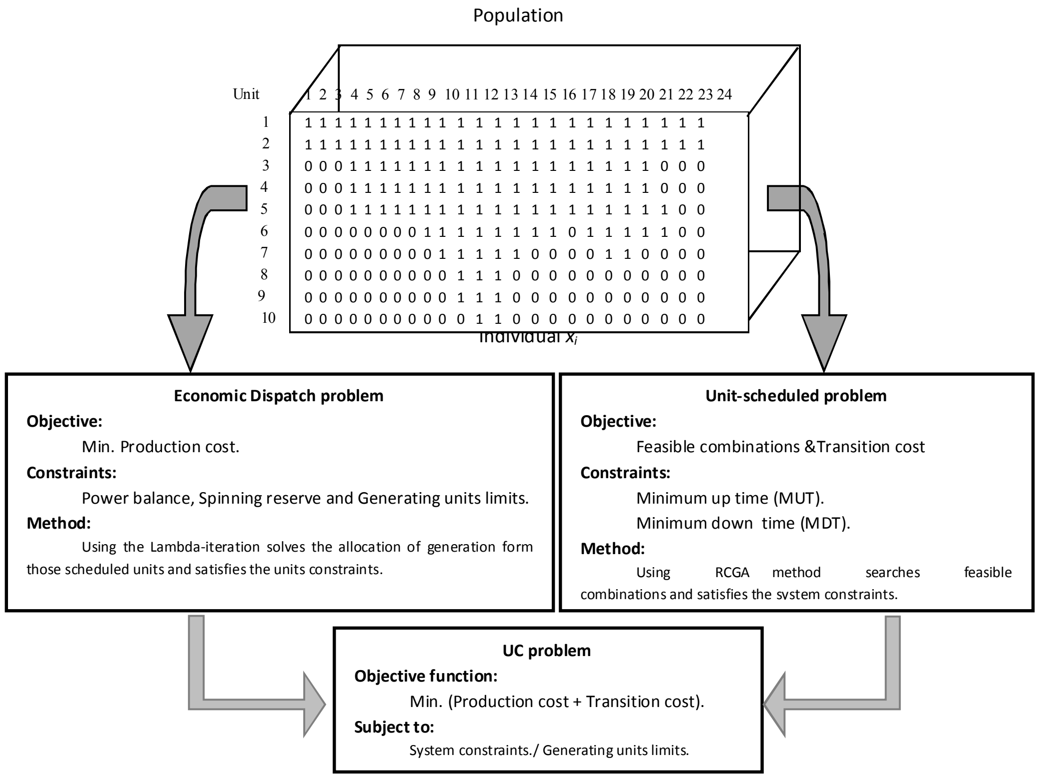


Figure VI.9 : *Binary representation of an individual xi in the population for a UC problem solution* [43].

Figure VI.9 shows a matrix representation of an individual xi in the population. When the size of the population is NP, the dimension of the population is equal to 10×24×NP. We can use the row values of the matrix to judge whether each scheduled-unit satisfies the MUT/MDT constraints, and to solve the transition cost during all scheduled period. We can use the column values to solve the ED solution and the production cost [43].

VI.3.2. Numerical tests :

The RCGA is applied to UC problems for realistic power systems of different sizes, along with hourly load demands. Also, their results are compared with those of previous works which used the same test. For each test case, 30 independent trials are conducted to compare the solution quality and convergence characteristics. The algorithm of this method was programmed in MATLAB environment and have been executed on a Pentium IV, 3-GHz computer with 4 GB RAM.

In all experiments, parameters of GA for experiments were as following: with mutation rate P_m of 0.3 and crossover rate P_c of 0.8 was used, initial population NP of size 40 was randomly created.

VI.3.2.1. *Test system 1 (Wood and Wollenberg 1996) :*

The algorithm was tuned using a small test problem (Wood and Wollenberg 1996) consisting of four units and a time horizon of eight hours and adding a quadratic fuel cost term. The new system has an optimal solution of $74,476.075. The system data is given in appendix. **7** (A.13 and A.14).

Table VI.7: Load distribution data for generator.

Unit	P_{min} MW	P_{max} MW	Hour 1	2	3	4	5	6	7	8
Unit 1	300	75	**300**	**300**	**300**	**300**	**300**	**255**	**265**	**300**
Unit 2	250	60	**150**	**205**	**250**	**215**	0	0	0	**200**
Unit 3	80	25	0	**25**	**30**	**25**	**80**	**25**	**25**	0
Unit 4	60	20	0	0	**20**	0	**20**	0	0	0
Load/MW			540	530	600	540	400	280	290	500
Hourly cost ($)			9145.3	10892.2	12570.5	11079.3	8531.8	5845.5	6024.7	10066.3
Start up cost ($)			0	150	0,02	0	0	0	0	170
Total cost ($)			**74,476.075**							

Table VI.8: Unit combination schedule.

	Hour 1	2	3	4	5	6	7	8
Unit 1	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
Unit 2	**1**	**1**	**1**	**1**	0	0	0	**1**
Unit 3	0	**1**	**1**	**1**	**1**	**1**	**1**	0
Unit 4	0	0	**1**	0	**1**	0	0	0

Table VI.9: Comparison with other conventional GA.

Methods	Total cost ($)
GA [202]	74,675
SGA	74,640.87
RCGA	74,476.07

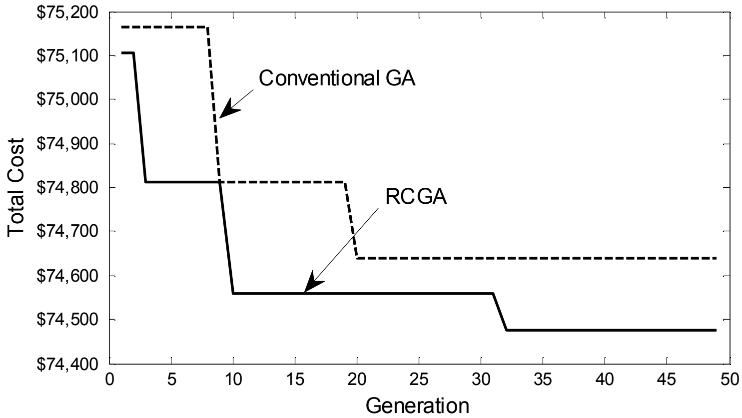


Figure VI.10 : *Typical performance of the RCGA versus the conventional GA.*

Fig. VI.10 shows results obtained by including the ring crossover operator it can be observed that the RCGA requires fewer generations to converge than the conventional GA. Table VI.7 gives the hourly and total cost distribution data of the 4─generator unit in an 8 hours' time period. for each hour, the expected output of each generator unit is evaluated, so that the load requirements are fulfilled. Table VI.8 presents the unit combination schedule for the test system, where 0 represents the *off* state and 1 the *on* state. Fig. V.11 shows the unit commitment schedule derived from this shut-down rule as applied to the hourly demands.

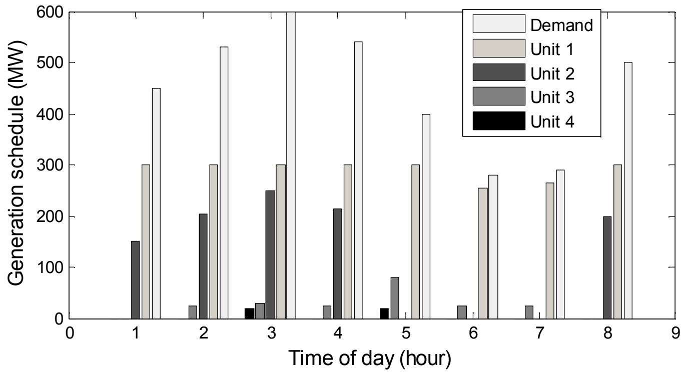


Figure VI.11 : *Unit commitment schedule.*

Tables VI.9 show the results of the proposed method comparing with other conventional GA method results, the obtained result in this section represents a nearer global optimal solution to the problem and verifies the correctness of the proposed algorithm.

VI.3.2.2. *Test system 2 (ten-unit):*

The proposed RCGA is initially tested on a simple ten-unit base system with a 24-h time horizon. The unit characteristics of the ten-unit system and the demand are given in appendix. 6 (A .11 and A.12, respectively).

In this simulation, the dimensions of an individual and a population are 10×24 and $10\times24\times40$, respectively.

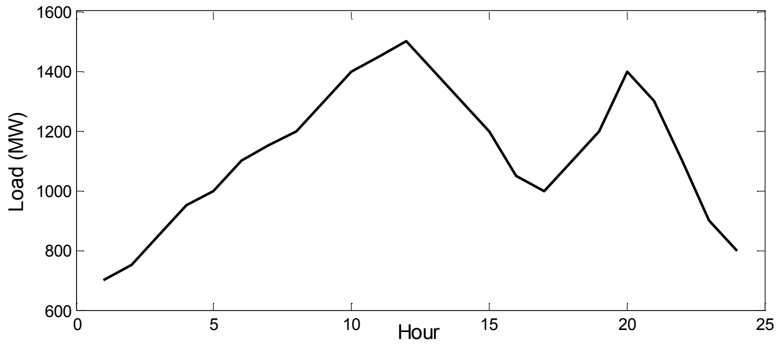


Figure VI.12 : *Load demand for 24 h.*

Table VI.10 shows the best combination of scheduled-units in the initial population. The total generation cost through the scheduling duration is \$572,798.24. Table VI.11 shows the simulation results including the production cost, transition cost, and spinning reserve capacity of each scheduling time interval, unit-scheduled for 24-hour duration and the total generation cost. The total generation cost of the best combination of scheduled-units is \$564,338. The load demand graph shown in fig. VI.12 has 5 sharp points including the first and the last hour values. Fig. VI.13 shows the convergence tendency of the best evaluation value in the population during RCGA processing with the conventional GA.

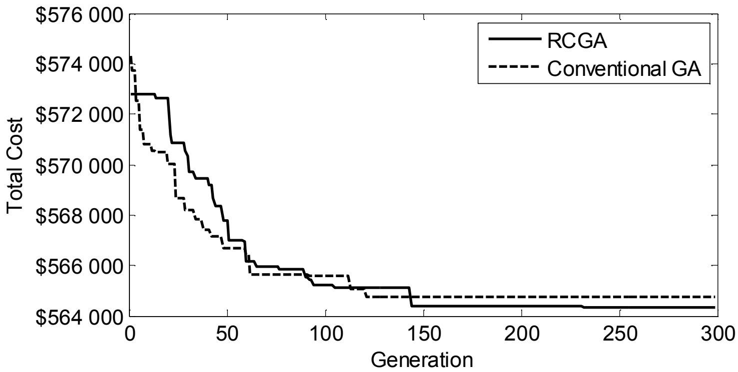


Figure VI.13 : *Typical performance of the RCGA versus the Conventional GA.*

Table VI.10: Best individual in the initial population.

Hour	Unit Schedule	Production Cost ($)	Transition Cost ($)	Spinning Reserve [MW]	Generation schedule (MW)									
					Unit 1	Unit 2	Unit 3	Unit 4	Unit 5	Unit 6	Unit 7	Unit 8	Unit 9	Unit 10
1	1100000000	13683.129	0	210	455	245	0	0	0	0	0	0	0	0
2	1100010000	15023.813	170	240	455	275	0	0	0	20	0	0	0	0
3	1101010000	17361.836	560	270	455	245	0	130	0	20	0	0	0	0
4	1101010100	19851.031	60	225	455	335	0	130	0	20	0	10	0	0
5	1111000000	20132.560	550	170	455	285	130	130	0	0	0	0	0	0
6	1111000001	22652.447	60	125	455	375	130	130	0	0	0	0	0	10
7	1111100000	23261.979	1800	182	455	410	130	130	25	0	0	0	0	0
8	1111111000	25341.600	690	297	455	415	130	130	25	20	25	0	0	0
9	1111111100	27967.301	60	252	455	455	130	130	75	20	25	10	0	0
10	1111111010	30075.859	60	152	455	455	130	130	162	33	25	0	10	0
11	1111111011	31944.521	60	157	455	455	130	130	162	73	25	0	10	10
12	1111111111	33890.162	60	162	455	455	130	130	162	80	25	43	10	10
13	1111111001	30086.010	0	152	455	455	130	130	162	33	25	0	0	10
14	1111111000	27251.056	0	197	455	455	130	130	85	20	25	0	0	0
15	1111110001	25378.508	30	267	455	430	130	130	25	20	0	0	0	10
16	1111100000	21513.659	0	282	455	310	130	130	25	0	0	0	0	0
17	1111100000	20641.824	0	332	455	260	130	130	25	0	0	0	0	0
18	1111100001	23160.316	60	287	455	350	130	130	25	0	0	0	0	10
19	1111100000	24150.340	0	132	455	455	130	130	30	0	0	0	0	0
20	1111110111	30883.379	320	177	455	455	130	130	162	38	0	10	10	10
21	1111110100	27303.219	0	167	455	455	130	130	100	20	0	10	0	0
22	1111110000	22855.552	0	312	455	340	130	130	25	20	0	0	0	0
23	1110000000	17795.281	0	140	455	315	130	0	0	0	0	0	0	0
24	1110000000	16052.851	0	240	455	215	130	0	0	0	0	0	0	0
Total		**568,258.24**	**4150**	**5127**	Total generation cost ($):				**572,798.24534**					

Table VI.11: Best individual by the proposed RCGA method.

Hour	Unit Schedule	Production Cost ($)	Transition Cost ($)	Spinning Reserve [MW]	Generation schedule (MW)									
					Unit 1	Unit 2	Unit 3	Unit 4	Unit 5	Unit 6	Unit 7	Unit 8	Unit 9	Unit 10
1	1100000000	13683.1297	0	210	455	245	0	0	0	0	0	0	0	0
2	1100000000	14554.4997	0	160	455	295	0	0	0	0	0	0	0	0
3	1100000001	17074.9447	60	115	455	385	0	0	0	0	0	0	0	10
4	1100100000	18597.6677	900	122	455	455	0	0	40	0	0	0	0	0
5	1101100000	20020.0195	560	202	455	390	0	130	25	0	0	0	0	0
6	1111100000	22387.0445	1100	232	455	360	130	130	25	0	0	0	0	0
7	1111100000	23261.9795	0	182	455	410	130	130	25	0	0	0	0	0
8	1111100000	24150.3407	0	132	455	455	130	130	30	0	0	0	0	0
9	1111111000	27251.0560	860	197	455	455	130	130	85	20	25	0	0	0
10	1111111010	30075.8593	60	152	455	455	130	130	162	33	25	0	10	0
11	1111111011	31944.5211	60	157	455	455	130	130	162	73	25	0	10	10
12	1111111111	33890.1629	60	162	455	455	130	130	162	80	25	43	10	10
13	1111111001	30086.0103	0	152	455	455	130	130	162	33	25	0	0	10
14	1111111000	27251.0560	0	197	455	455	130	130	85	20	25	0	0	0
15	1111100000	24150.3407	0	132	455	455	130	130	30	0	0	0	0	0
16	1111100000	21513.6595	0	282	455	310	130	130	25	0	0	0	0	0
17	1111100000	20641.8245	0	332	455	260	130	130	25	0	0	0	0	0
18	1111100000	22387.0445	0	232	455	360	130	130	25	0	0	0	0	0
19	1111100000	24150.3407	0	132	455	455	130	130	30	0	0	0	0	0
20	1111111100	30057.5503	490	152	455	455	130	130	162	33	25	10	0	0
21	1111111000	27251.0560	0	197	455	455	130	130	85	20	25	0	0	0
22	1100111000	22735.5210	0	137	455	455	0	0	145	20	25	0	0	0
23	1100010000	17645.3637	0	90	455	425	0	0	0	20	0	0	0	0
24	1100000000	15427.4197	0	110	455	345	0	0	0	0	0	0	0	0
Total		**560,188.412**	**4150**	**4168**	Total generation cost ($):				**564,338.4127**					

Fig. VI.11 shows a comparison of production cost at each hour between the best individual in the initial population and best individual of all generations by the proposed RCGA method.

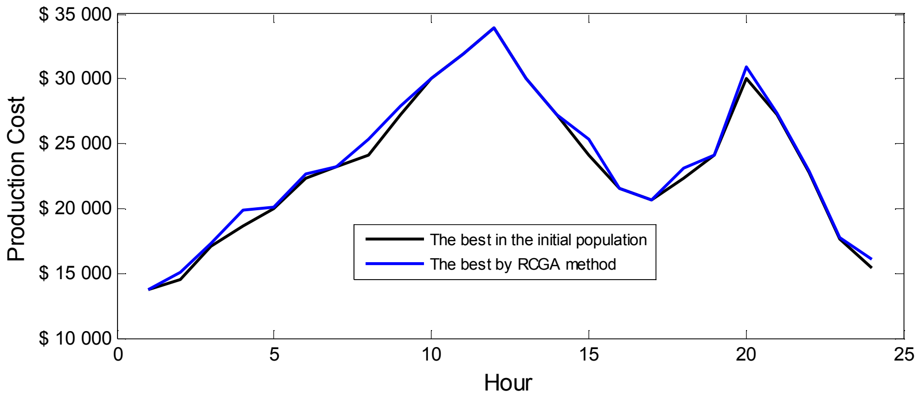


Figure VI.14 : *Comparison of fuel cost.*

Fig. VI.15 shows the results of unit commitment optimization problem for ten-unit system by the proposed RCGA with a 24-h time horizon. In fig. VI.14, the amount of generators' supply curve for each unit are normalized according to their maximum generation power during an hour.

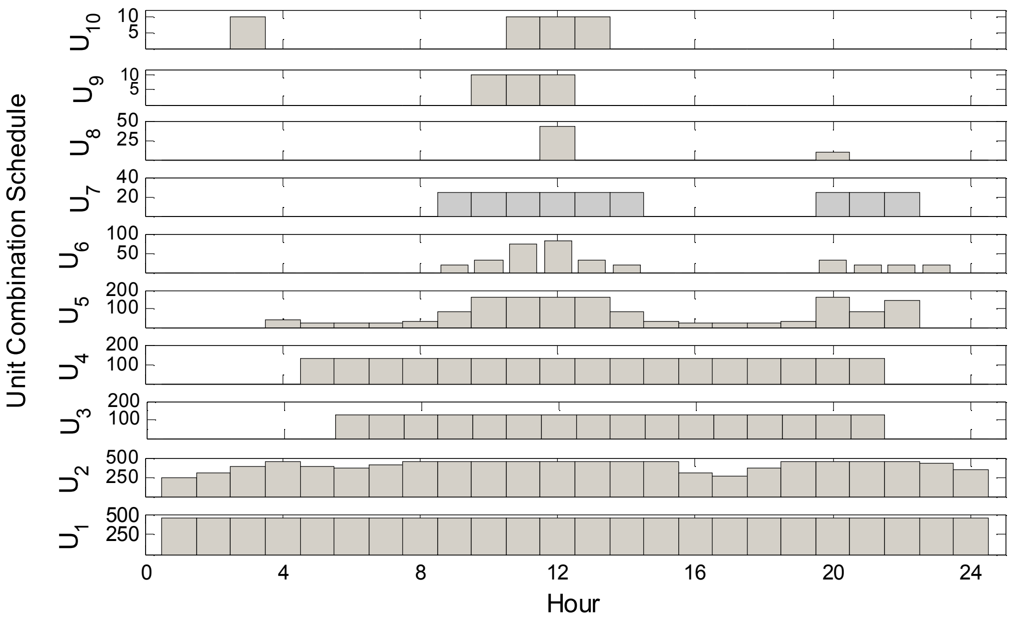


Figure VI.15 : *The output data for all 15 units.*

To show the advantages of the proposed method, we will compare the performance of the proposal method with conventional GA and another GA methods [202], [58], [43], [201–180] and [183–36] in table VI.12.

Table VI.12 : Comparison of solution quality with other GA methods.

Methods	Best generation cost ($)	Average generation cost ($)	Worst generation cost ($)	Standard deviation (%)	The computation time (sec.)
GA [202]	565,866	567,329	571,336	0.26 (%)	113
GA [43]	570,781	574,280	576,791	1549.9 ($)	62.29
GA [201]	609,023.69	—	—	—	73.68
SGA [180]	565,121	—	622,846	9.27 (%)	462.31
TLGA [180]	564,426	—	566,182	0.31 (%)	439.313
FPGA [183]	564,094	566,675	569,237	0.33 (%)	—
GA [58]	565,825	—	—	—	—
ICGA [184]	566,404	—	—	—	—
RCGA	**564,338.41**	566,997.62	569,637.25	0.34 (%)	85.12

Sign (—) means that no amount has been reported.

VI.3.2.3. *Large-scale UC problem (20, 40, 60, 80, and 100 units):*

To verify the effectiveness and efficiency of the proposed RCGA method in solving large-scale UC problem, the proposed method is applied on 20-100 unit systems, the 20, 40, 60, 80, and 100 units data are obtained by duplicating the base case (ten units), whereas the load demands are adjusted in proportion to the system size. In the simulation, the reserve is required to be 10% of the load demand. The statistical results obtained by different algorithms are shown in table VI.13, from the simulation results, it is very evident that RCGA not only has found the highest quality results among the all algorithms compared. The best UC schedule of the tests systems on 24-h scheduling horizon with one-hour interval are shown in the tables VI.14, VI.15, VI.16, VI.17 and VI.18. To illustrate the convergence property of the proposed algorithm, fuel cost values over 300 iterations for 20 units systems are plotted in fig. VI.16.

Table VI.13 : Comparison of total production costs.

Units	Total production costs ($)						
	LR[58]	GA[58]	EP[189]	LRGA[191]	GAUC[203]	DPLR[204]	RCGA
20	1,130,660	1,126,243	1,125,494	1,122,622	1,125,516	1,128,098	1,125,141
40	2,258,503	2,251,911	2,249,093	2,242,178	2,249,715	2,256,195	2,250,286
60	3,394,066	3,376,625	3,371,611	3,371,079	3,375,065	3,384,293	3,370,588
80	4,526,022	4,504,933	4,498,479	4,501,844	4,505,614	4,512,391	4,501,739
100	5,657,277	5,627,437	5,623,885	5,613,127	5,626,514	5,640,488	5,627,432

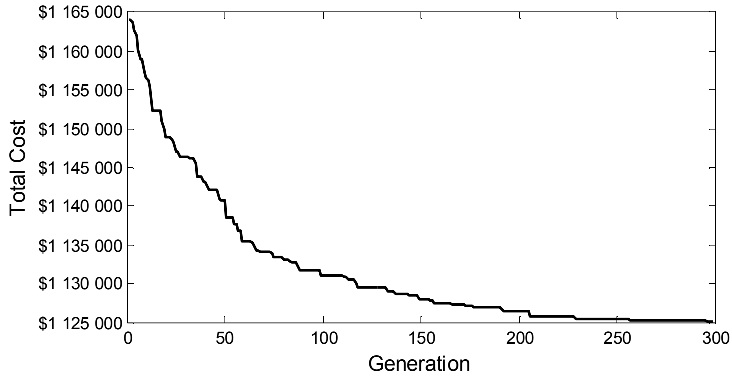


Figure VI.16 : *Convergence characteristic of fuel cost using RCGA for 20-units.*

Table VI.14 : The best unit schedule generated using proposed method for 20 unit system.

Hour	Demand (MW)	Commitment schedule	Generation cost ($/h)
1	1400	11110000000000000000	27,366.25
2	1500	11110000000000000000	29,108.99
3	1700	11110000100000000000	34,011.24
4	1900	11111000100000000000	37,778.60
5	2000	11111010100000000000	40,123.83
6	2200	11111011100100000000	45,578.40
7	2300	11111011110100000000	48,226.51
8	2400	11111111110100000000	49,844.13
9	2600	11111111111101000000	54,698.77
10	2800	11111111111111100010	60,783.56
11	2900	11111111111111111010	63,962.27
12	3000	11111111111111111111	67,900.32
13	2800	11111111111111000101	60,161.86
14	2600	11111111111100000010	53,950.44
15	2400	11111111110000000000	48,300.68
16	2100	11111111110000000000	43,027.31
17	2000	11111111110000000000	41,283.64
18	2200	11111111110000000000	44,774.08
19	2400	11111111110000000000	48,300.68
20	2800	11111111111100011111	61,715.51
21	2600	11111111111100001000	53,910.29
22	2200	11111110101100000000	44,617.15
23	1800	11110000100000000000	34,862.50
24	1600	11110000000000000000	30,854.83

Table VI.15 : The best unit schedule generated using proposed method for 40 unit system.

Hour	Demand (MW)	Commitment schedule (Unit 1 to 40)	$Cost_T$ ($/h)
1	2800	1111111100000000000000000000000000000000	54,732.51
2	3000	1111111100000000000000000000000000000000	58,217.99
3	3400	1111111100000000101100000000000000000000	69,430.08
4	3800	1111111100001000101100000000000000000000	74,879.58
5	4000	1111111101011010111100000000000000000000	82,702.36
6	4400	1111111111011111111100000000000000000000	92,270.50
7	4600	1111111111011111111100000000000000000000	92,434.27
8	4800	1111111111111111111100000000000000000000	97,701.36
9	5200	1111111111111111111110100110000000000011	110,187.5
10	5600	1111111111111111111111111111000100000111	122,155.5
11	5800	1111111111111111111111111111000011111111	128,078.0
12	6000	1111111111111111111111111111111111111111	135,770.6
13	5600	1111111111111111111111111011110110010000	120,353.7
14	5200	1111111111111111111110111010000000000000	107,269.4
15	4800	1111111011111111111100001000000000000000	96,988.10
16	4200	1111111011111111111100000000000000000000	85,432.93
17	4000	1111111011111111111100000000000000000000	81,941.56
18	4400	1111111011111111111100000000000000000000	88,930.50
19	4800	1111111011111111111100010001000000000000	97,833.59
20	5600	1111111111111111111111111011000011111000	122,468.8
21	5200	1111111110111111111111111011000000000000	108,120.7
22	4400	1111111100001101011111010100000000000000	89,390.13
23	3600	1111111110000000001000000000000000000010	70,665.18
24	3200	1111111110000000000000000000000000000000	62,331.18

Table VI.16 : The best unit schedule generated using proposed method for 60 unit system.

Hour	Demand (MW)	Commitment schedule (Unit 1 to 60)	Generation cost ($/h)
1	2800	111111111110000000000000000000000000000000000000000000000000	82,098.77
2	3000	111111111110000000000000000000000000000000000000000000000000	87,326.99
3	3400	111111111110000000000001110100000000000000000000000000000000	103,441.3
4	3800	111111111110000000100001111100000000000000000000000000000000	112,902.2
5	4000	111111111111010101010010111111000000000000000000000000000000	122,738.9
6	4400	111111111111111111010110111111000000000000000000000000000000	136,986.5
7	4600	111111111111111111010111111111000000000000000000000000000000	139,527.7
8	4800	111111111111111111011111111111001000000000000000000000000000	146,520.7
9	5200	111111111111111111111111111111111111010010000000000000001111	165,250.0
10	5600	111111111111111111111111111111111111111111100000000010101110	183,185.2
11	5800	111111111111111111111111111111111111111111000000111111011111	191,342.1
12	6000	111111111111111111111111111111111111111111111111111111111101	203,045.7
13	5600	111111111111111111111111111111111111011011101100100111000100	180,621.2
14	5200	111111111111111111111111111111111101001100100000001000000000	161,463.0
15	4800	111111111111111111110111111111010000000000000000000000000000	145,060.7
16	4200	111111111111111111110111111111000000000000000000000000000000	128,490.9
17	4000	111111111111111111110111111111000000000000000000000000000000	123,255.9
18	4400	111111111111111111110111111111000000000000000000000000000000	133,735.2
19	4800	111111111111111111110111111111010000000000000000000000000000	145,230.7
20	5600	111111111111111111111111111111111111111001100100111011010000	184,169.5
21	5200	111111111111111111111111111111101111111110010000000000000000	161,770.4
22	4400	111111111111100001011001100101011111110010000000000000000000	134,446.1
23	3600	111111111110000001010001100000000000000000000000000000000000	105,247.5
24	3200	111110111110000000010001000000000000000000000000000000000000	92,730.84

Table VI.17 : The best unit schedule generated using proposed method for 80 unit system.

Hour	Commitment schedule (Unit 1 to 80)	Generation cost ($/h)
1	11111111111111100000010000000000000000000000000100000000000000000000000000000000	111,283.97
2	11111111111111100000010000000000000000000000001100000000000000000000000000000000	118,169.72
3	11111111111111100000010001000000101010100010011000000000000000000000000000000000	139,386.44
4	11111111111111100000010001000001101010100010010000000000000000000000000000000000	149,998.39
5	11111111111111110110011010101010111111010001000000000000000000000000000000000000	165,375.29
6	11111111111111110110111011101111110100000000000000010000000000000000000000000000	180,169.09
7	11111111111111110110111011111110111111010000000100000010000000000000000000000000	186,003.96
8	11111111111111111101110111111111111111100000010000001000000000000000000000000010	198,547.60
9	11111111111111111101111111111111111111110111011010000010001000000000000101001100	219,956.29
10	11111111111111111111111111111111111111111111111111101111001000010000000101101110	244,605.82
11	11111111111111111111111111111111111111111111111111111111001101111000110111001111	255,709.48
12	11111111111111111111111111111111111111111111111111111111111111111111111111011111	270,916.03
13	11111111111111111111111111111111111111111111111110111111110010001001000100010001	239,967.05
14	11111111111111111111111111111111111111111101011110000100000000001001000100001000	215,569.06
15	11111111111111111110111011101111111111111010001100000000000000000000000000000000	194,059.49
16	11111111111111111110111011101111111111110000000000000000000000000000000000000000	170,277.26
17	11111111111111111110111011101111111111110000000000000000000000000000000000000000	163,290.49
18	11111111111111111110111011101111111111110001000000000000000000000000000000000000	177,914.23
19	11111111111111111110111011101111111111110001001100000000000000000000000000000001	194,792.04
20	11111111111111111111111111111111111111111111111100111011100101011100111100000010	246,540.22
21	11111111111111111111111111111111111111110111110111001110110000000000000000000000	215,201.37
22	11111111111111100010111111010010001010111011000011101100000000000000000000000000	178,490.33
23	11111111101111100010011011100001000100000000000000000000000000000000000000000000	141,113.78
24	11111111100111110001000100010000100010000000000000000000000000000000000000000000	124,402.10

Table VI.17 : The best unit schedule generated using proposed method for 80 unit system.

Hour	Commitment schedule (Unit 1 to 80)	Generation cost ($/h)
1	11111111111111100000010000000000000000000000000100000000000000000000000000000000	111,283.97
2	11111111111111100000010000000000000000000000001100000000000000000000000000000000	118,169.72
3	11111111111111100000010001000000101010100010011000000000000000000000000000000000	139,386.44
4	11111111111111100000010001000001101010100010010000000000000000000000000000000000	149,998.39
5	11111111111111110110011010101010111111010001000000000000000000000000000000000000	165,375.29
6	11111111111111110110111011101111110100000000000000010000000000000000000000000000	180,169.09
7	11111111111111110110111011111110111111010000000100000010000000000000000000000000	186,003.96
8	11111111111111111101110111111111111111100000010000001000000000000000000000000010	198,547.60
9	11111111111111111101111111111111111111110111011010000010001000000000000101001100	219,956.29
10	11111111111111111111111111111111111111111111111111101111001000010000000101101110	244,605.82
11	11111111111111111111111111111111111111111111111111111111001101111000110111001111	255,709.48
12	11111111111111111111111111111111111111111111111111111111111111111111111111011111	270,916.03
13	11111111111111111111111111111111111111111111111110111111110010001001000100010001	239,967.05
14	11111111111111111111111111111111111111111101011110000100000000001001000100001000	215,569.06
15	11111111111111111110111011101111111111111010001100000000000000000000000000000000	194,059.49
16	11111111111111111110111011101111111111110000000000000000000000000000000000000000	170,277.26
17	11111111111111111110111011101111111111110000000000000000000000000000000000000000	163,290.49
18	11111111111111111110111011101111111111110001000000000000000000000000000000000000	177,914.23
19	11111111111111111110111011101111111111110001001100000000000000000000000000000001	194,792.04
20	11111111111111111111111111111111111111111111111100111011100101011100111100000010	246,540.22
21	11111111111111111111111111111111111111110111110111001110110000000000000000000000	215,201.37
22	11111111111111100010111111010010001010111011000011101100000000000000000000000000	178,490.33
23	11111111101111100010011011100001000100000000000000000000000000000000000000000000	141,113.78
24	11111111100111110001000100010000100010000000000000000000000000000000000000000000	124,402.10

Table VI.18 : The best unit schedule generated using proposed method for 100 unit system.

Hour	Commitment schedule (Unit 1 to 100)	Generation cost ($/h)
1	1111111111111111111110000000000000000000100010001000000000000000000000000000000000000000000000000000	142,239.92
2	1111111111111111111110000000000000000000100010001000000000000000000000000000000000000000000000000000	147,697.26
3	1111111111111111111110001000001000000010110011011001000100000000000000000000000000000000000000000000	174,126.98
4	1111111111111111111110001000001000000010110011011001000100000000000000000000000000000000000000000000	186,908.86
5	1111111111111111111110001000001010001010110011011101000100000000000000000000000000000000000000000000	199,364.02
6	1111111111111111111111111110001011001010111011011101000100000000000000000000000000000000000000000000	227,689.76
7	1111111111111111111111111110001111111010111011011101000101000000000010000000000000000000000000000000	235,365.78
8	1111111111111111111111111110001111111111111110111101000111000000000010000000000000000000000000010000	247,740.15
9	1111111111111111111111111111111111111111111111111111111011111100000101010000000000000000000001001000	276,908.79
10	1111111111111111111111111111111111111111111111111111111111111111111111000100001100010100100001001000	303,643.00
11	1111111111111111111111111111111111111111111111111111111111111111111111100001111110111111000011101100	318,595.03
12	1111111111111111111111111111111111111111111111111111111111111111111111111111111111111111111111011101	338,131.15
13	1111111111111111111111111111111111111111111111111111111111111011101111001000111001000100010000110011	300,316.23
14	1111111111111111111111111011111111111111111111111111111111111010001000000000000001000000000000000000	268,414.45
15	1111111111111111111110111101001111111110111111111100101100110000001000000000100000000000000000000000	243,663.43
16	1111111111111111111110111101001111111110111111111100000100000000000000000000000000000000000000000000	212,533.97
17	1111111111111111111110111101001111111110111111111100000100000000000000000000000000000000000000000000	203,796.09
18	1111111111111111111110111101001111111110111111111100000100000000000000000000000000000000000000000000	221,287.35
19	1111111111111111111110111110011111111110111111111101110100000000000001000000000000000000000000000000	244,076.68
20	1111111111111111111111111111111111111111111111111111111111110011011011000100011100111010010101101110	307,336.64
21	1111111111111111111111111111111111111111101110111111111111110011011011000000000000000000000000000000	269,046.02
22	1111111111111111111110100111110100011011001110111110101011110011011010000000000000000000000000000000	224,536.20
23	1111111111111011111101001010110000000010011110001000001000000000000000000000000000000000000000000000	177,012.96
24	1111011111101011111101001000110000000010011110001000000000000000000000000000000000000000000000000000	157,001.22

VI.4. Conclusion :

In this chapter, the proposed RCGA is efficiently and effectively implemented to solve the UC problem. RCGA total production costs over the scheduled time horizon are less expensive than conventional GA, especially on the large number of generating units. The proposed algorithm considered various constraints successfully and the genetic operations are improved based on the characteristic of power system. The test results demonstrate the effectiveness of the RCGA in searching global or near global optimal solution to the UC problem. Also the results show a better convergence and higher precision.

CHAPTER VII

A novel Meta-heuristic methods and its application in solution of the ED and UC problems

VII.1. Introduction

In this chapter we introduce a new method for optimization that is called root tree optimization algorithm (RTO), the robustness and efficiency of the proposed new method is validated on nonlinear functions and compared to recent methods addressing the same problem, simulation results confirm efficiency and reliability of the proposed RTO algorithm for solving complex optimization problem in term of solution quality and convergence characteristic.

The proposed approach RTO has been applied to various test systems with incremental fuel cost function, taking into account the valve-point effects, the simulation results obtained by the proposed algorithms are compared with the results obtained using other recently develop methods available in the literature, from numerical results, it is found that the proposed RTO approach is able to provide better solution than other reported techniques in terms of fuel cost, furthermore, this algorithm is better in terms of robustness than most of the existing algorithms used in this study.

The second part of the chapter proposed a novel operator for Genetic Algorithms a "genetic modification" for solving the UCP, generating unit's shows that we can find the optimal solution effectively and these results are compared with the conventional methods and various optimization approaches in the recent literature.

The proposed algorithm GAGE is efficiently applied to solve the UCP, the total production costs of GAGE over the scheduled period are less expensive than the conventional genetic algorithm and the algorithms proposed the recent literature. The total production costs of GAGE over the scheduled period are less expensive than the conventional genetic algorithm and the algorithms proposed the recent literature.

VII.2. A new rooted tree optimization algorithm for ED problem :

In the latest twenty years, the artificial intelligence started to be oriented to the simulation of nature, to the way how the human brain functions and the human operations thinking. Consequently, a new branch of this artificial intelligence (CI) has emerged which studies and designs the intelligent implements that adapt intelligently with their environment and they show an cognitive behavior whereas they became able to take decision through the recuperation of the acquired information. This intelligence considers the human being as an example of these implements, the arithmetic intelligence contains: the evaluating computing, fuzzy computing and the neural computing.

At the beginning of the ninetieth years from the last Century, the researches started to be oriented forwards by simulating the less clever creatures which have a limited capacities as: the pants, the birds and fishes that show, at the same time, a so clever social behavior, in 1990, Diarogo suggested an algorithm of ant colony optimization ACO which simulates the ants settlements. In 1995, both of Rusell Eberth and James Kendy suggested an algorithm of practical swarm optimization PSO that depends totally on the simulation of the birds swarms. The two previous algorithms PSO and ACO were a starting point to a new branches of the swarm intelligence SI, the most important characteristics of these new branches CI and SI are their dependent on the digital treatment, they are not based on the mathematical knowledge, both of CI and SI are considered as a complex of algorithms composed of: a specific steps, a known start and an end point that led to solve the problem.

Even with the great enhancement of the computing capacities, there are difficult problems. Fortunately, many sensitive research algorithms are developed to find a suitable solution to these problems at a reasonable time; they are developed according to the evolution of the physiology and biology. One of them is the genetic algorithm GA and simulated annealing SA, these techniques are used to solve many problems widely.

In this section we introduce a new method that is called (rooted tree optimization) because it is extracted from the movement of the plants root when they look for the nearest place of water, in this algorithm we lean on the behavior of the desert plants especially where the water resources lacked. If the vegetal scientist or the biologists allow, we can say that the desert root plants smell the places of water (here, we find the intuitive behavior) around it, where these places present the optimal solution for us, to determine it we use a group of roots which oriented by a special conducting.

In this section we are attempting to introduce an algorithm RTO based on that intuitive behavior which leads to the water location and has an oriented movement when it looking for the best solution.

Unlike classical search and optimization methods, RTO starts its search with a random set of solutions (group of roots), instead of a single solution just like GA. Each population member is then evaluated for the given objective function and is assigned fitness. The best fits are entertained for the next generation while the others are discarded and compensated by a new set of random solutions in each generation. The far solution from the water place is omitted or replaced by a new roots oriented randomly, also it is replaced by roots near from the best root of the previous generation. The only stopping criterion is the completion of maximum number of cycles or generations. At the end of the cycles, the solution of the best fitness is the desired solution.

The main objective of this study is to present the use of the RTO technique to the subject of the ED in power systems. In this section, the RTO method has been proposed to solve the ED problem with valve-point effect for 3, 6 and 13 units test systems. In general terms, the contribution of this paper is the new efficient RTO approach for the ED problem with valve-point effect. The results obtained with the proposed RTO approach were analyzed and compared other with optimization results reported in literature.

VII.2.2. Method Rooted tree optimization algorithm (RTO) :

VII.2.2.1. *The roots look for water :*

One root has a limited capacity, but a group of roots can find together the best issues to get water, and the majority of them are located around this issue or around the way that links the plant with the resource of water. To create the algorithm, we add a hypothetical behavior which is the way how the roots decide together to choose the orientation according to the witness degree where the root head is located, these ones move randomly but when they find the wetness they contact between them to intensify their existence around this way, so it becomes a new start point for the majority of the root group to get the original place of water.

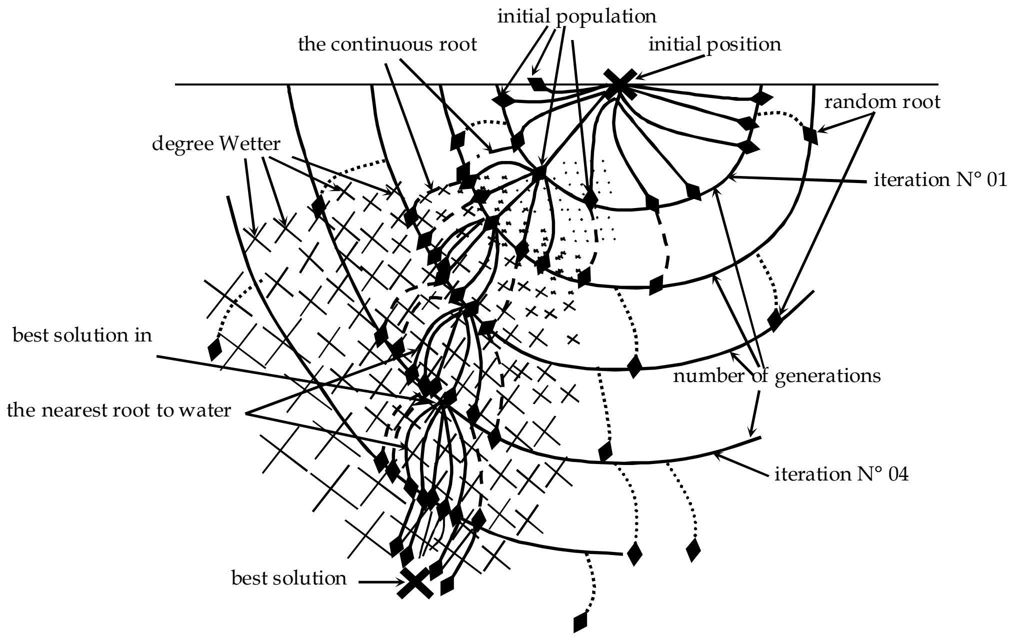


Figure VII.1 : *the roots of plants behavior when they look for water (the solution).*

The Fig. VII.1 presents the way how the roots of plants behave when they look for water -the solution- according to what we have talked about in RTO, where we find that the far solution from the water place (which has a less witness degree) is omitted or replaced by a new roots oriented randomly, also it is replaced by roots near from the best root of the previous generation, whereas the roots which have a considerable witness degree preserve their orientation, where we remark that the majority of roots gather at the last step next to the best solution- resource of water-.

VII.2.2.2. *Rooted tree optimization method :*

The proposed method is similar to the most other methods it begin by creating an initial population randomly. But before that, we will introduce some terms which will determine the method of moving from initial population to the new population:

- *Root*: is a candidate or the suggested solution.
- *Degree Wetter* D_w: it is a term that evaluates the candidate and gives him his optimization degree between the rest of population, it seems to the mechanism fitness, it is calculated using the equation (VII.4).

A. *The rate of the nearest root to water R_n*

It is the rate that represents the number of candidates according to the total population that should gather around the wetness or the wetter place (the best solution to the previous generation). It will be the successor of the roots which were in a dry places (in the witness is so weak) from the previous generation. The new population of the nearest root to water is calculated according to the formula:

$$x^{new}(i,It+1) = x^{best}(It) + c_1 \times D_w(i) \times randn \times l/(N \times It) \quad \text{(VII.1)}$$

Where It is the iteration step, $x^{new}(It+1)$ is the new candidate for the iteration $(It+1)$, $x^{best}(It)$ is the best solution to the previous generation, *i* is the number of candidate, N is the population scale, l is the upper limit of the parameter and *randn* is a normal random number between [-1, 1]. Then new point x^{new} is upper and lower bounded.

B. *The rate of the continuous root in its orientation R_c*

It is the rate of the members that continued the previous way because it appears near from water. The new population of the random root is calculated according to the formula:

$$x^{new}(i,It+1) = x(i,It) + c_2 \times D_w(i) \times rand \times (x^{best}(It) - x(i,It)) \quad \text{(VII.2)}$$

Where $x(It)$ is the previous candidate for the iteration It and $rand$ is random number between [0, 1].

C. *The rate of the random root R_r*

It is the rate that represents the number of candidates according to the total population that we want that they spread randomly in the research field in order to increase the rate of getting the global solution, it replaces also the roots in the wetness degree is so wick (weak candidates) from the last generation. The new population of the random root is calculated according to the formula:

$$x^{new}(i,It+1) = x_r(It) + c_3 \times D_w(i) \times randn \times l/It \quad \text{(VII.3)}$$

Where x_r is individual randomly selected from the previous generation, c_1, c_2 and c_3 is the adjustable parameters.

The rates R_n, R_r and R_c are determined by the experiments according to the exposed problem, these rates are considered as a variables which affect the convergence and how to find solution. The rate R_r is always small in comparison with the rest because it aims to reserve the random in order to be far from the local, its role can be presented as a mutation in the genetic algorithm.

We put the D_w value in the research functions of the roots in order to determine a space research according to the candidate power. When his power increase (presented by the D_w values), our goal is to, assure the step and the type of the used relation to create a new generation.

VII.2.2.3. *The algorithm RTO :*

Summarizing the steps in RTO yields to:

Step 1: Creation of primary generation randomly which is composed from N candidate with the respect of the variables limits in the research space, and the determination of the rates values R_n, R_r and R_c.

Step 2: We evaluate all the population members in order to measure the witness degree D_w by using the objective function following this formula:

$$D_w(i) = \begin{cases} \dfrac{f_i}{\max(f_i)} & \text{for the maximum objective} \\ 1 - \dfrac{f_i}{\max(f_i)} & \text{for the minimum objective} \end{cases} \quad , \quad i = 1,2,\ldots,N \quad \text{(VII.4)}$$

Or we use directly the fitness regardless of the suitable formula.

Step 3: Reproduction and replacement by the new population;

We reorder the population according to the degree wetter D_w in order to replace them by the new population according to R_n, R_r and R_c as the following:

$D_w = 0$	$x_{new}(i, it+1) = x_r + c_3 * D_W(i) * randn * l / it$	For $i = 1, \ldots, N*R_r$
↑	$x_{new}(i, it+1) = x^{best}(it) + c_1 * D_W(i) * randn * l / (N*it)$	For $i = N*R_r + 1, \ldots, N*(R_n + R_r)$
$D_w = 1$	$x_{new}(i, it+1) = x(i, it) + c_2 * D_W(i) * rand * (x^{best}(it) - x(i, it))$	For $i = N*(R_n + R_r) + 1, \ldots, N$

Where $R_n + R_r + R_c = 1$. We start by the candidate which has the less D_w till we get at the one who has a degree wetter equivalent 1.

Step 4: Return to *step* 2 if the stopping criteria is not realized.

The RTO algorithm is a method based on the most of the meta-heuristic algorithms; it is a simple evolutionary algorithm that creates new candidate solutions by integrating the parent individual with several other individuals in the same population. All candidates replace the parent, the rooted tree optimization algorithm is written as the Algorithm.1 represent the recreation of the new generation concerning the algorithm RTO.

Algorithm.1. RTO Algorithm

//Initialization:
Set the rates R_n, R_r and R_c parameters;
Give the maximum number of iterations, MaxIte, the population scale is $theRTOsize$;
Set iteration counter it =1;
For *i=1* **to** $theRTOsize$ **do**
 Generate the initial population X_i randomly within the search range of ($X_{\min}$, $X_{\max}$);
end for
Evaluate the fitness for each individual D_{W_i};
Reorder the population according to the witness degree;
Identify the candidate according the wetness place (the best solution) X_{best};
//Loop:
While *(stop criterion is not satisfied & it < MaxIte)* **do**
 For $i=1$ **to** $R_r \times theRTOsize$ **do**
  Selected individual X_r^{it} randomly from the current population;
  $X_i^{it+1} = X_r^{it} + c_1 \times D_{W_i} \times randn \times |X_{\max} - X_{\min}| / (it)$;
 end for
 For $i = R_r \times theRTOsize+1$ **to** $(R_r + R_n) \times theRTOsize$ **do**
  $X_i^{it+1} = X_{best} + c_3 \times D_{W_i} \times randn \times |X_{\max} - X_{\min}| / (theRTOsize \times it)$;
 end for
 For $i = (1 - R_c) \times theRTOsize+1$ **to** $theRTOsize$ **do**
  $X_i^{it+1} = X_i^{it} + c_1 \times D_{W_i} \times rand \times (X_{best} - X_i^{it})$;
 end for
 Evaluate fitness D_{W_i} for each candidate;
 Update X_{best};
 it = it + 1;
end while

From the Fig. VII.2 we remark the change of the parameters x_1 and x_2 according to the generation number where the three kinds of roots appear, these kinds represent the random roots, and the roots which meet together till they stop these ones represent the near roots from the solution, the rest kind represent those groups which cease when they become weak in comparison with the other roots of the same generation. It appears so clear in the Fig. VII.3 which represents evaluation the Rastrigin function (N=2) (where N is the number of dimension) where the majority of roots gather in the solution -resource of water-.

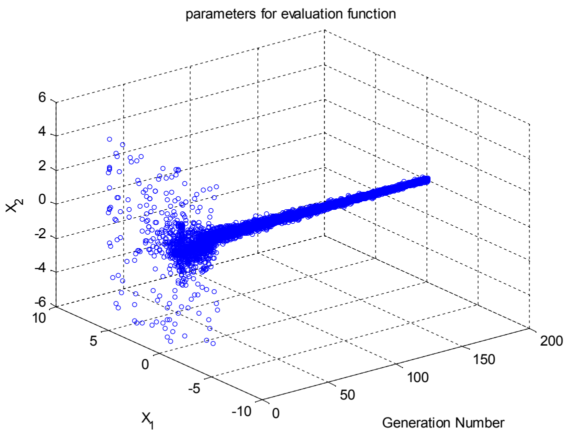


Figure VII.2 : *The parameters and the roots for 200 iterations (the Rastrigin function (N=2)).*

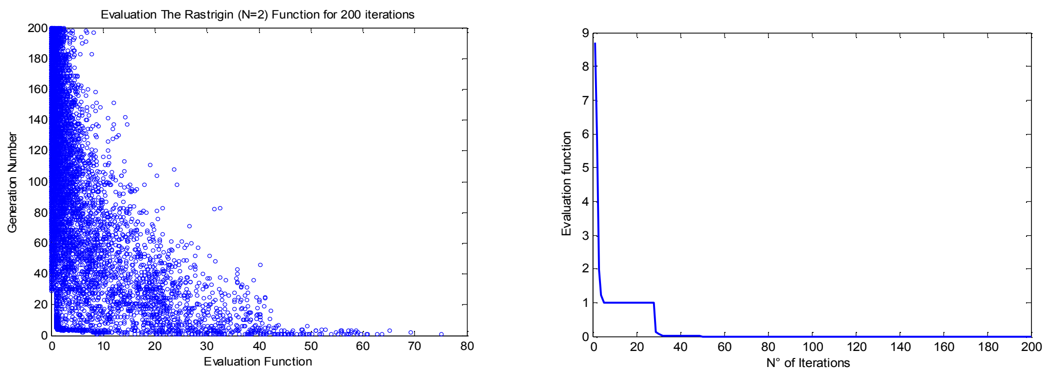


Figure VII.3 : *Evaluation The Rastrigin function (N=2) for 200 iterations.*

We remark in the Fig. VII.4 the concentration of the roots (candidates) with the different rates R_n, R_c and R_r where we can see how every kind looks for water through changing the rates values, so the convergence to the solution has a strong relation with the different behaviors movements of the roots kinds between them as we have listed previously.

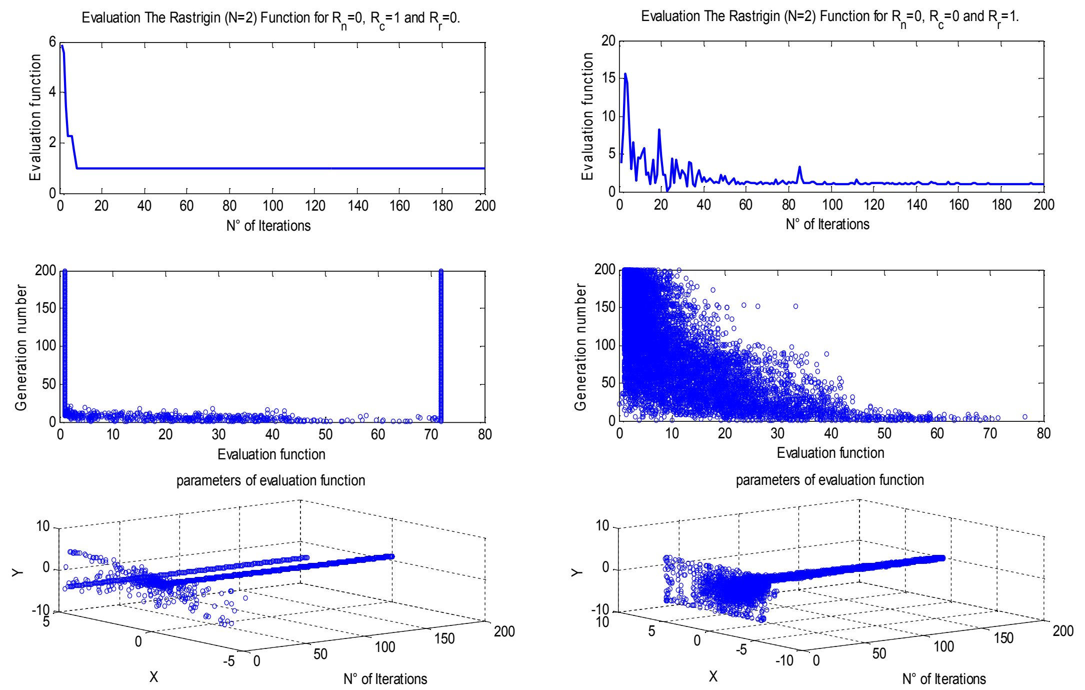


Figure VII.4 : *Evaluation the Rastrigin function for different rates parameters; R_n, R_r and R_c.*

Algorithm.2. RTO Modified Algorithm (RTO$_M$)

//Initialization:
Set the rates R_n, R_r and R_c parameters;
Give the maximum number of iterations, MaxIte, the population scale is theRTOsize;
Set iteration counter it =1;
Generate the initial population X_i randomly within the search range of (X_{min}, X_{max});
Evaluate the fitness for each individual Dw_i ;
Reorder the population according to the witness degree;
Identify the candidate according the wetness place (the best solution) X_{best};
//Loop:
While *(stop criterion is not satisfied & it < MaxIte)* **do**

For i =*1* **to** *theRTOsize* **do**

If $Dw_i < R_r$ **do**

Selected individual X_r^{it} *randomly from the current population;*

$$X_i^{it+1} = X_r^{it} + c_1 \times Dw_i \times randn \times \mid X_{\max} - X_{\min} \mid /(it);$$

Else if $Dw_i < R_c$ **do**

$$X_i^{it+1} = X_{best} + c_3 \times Dw_i \times randn \times \mid X_{\max} - X_{\min} \mid /(theRTOsize \times it);$$

Else

$$X_i^{it+1} = X_i^{it} + c_1 \times Dw_i \times rand \times (X_{best} - X_i^{it});$$

end If

end If

Evaluate fitness Dw_i for each candidate;

Update X_{best};
it = it + 1;

end while

We suggest the Algorithm.2 which is the same as the other only in the number of roots of each kind, where its number changes at any step (iteration) because the number of each kind is not stable, but it's likened to the degree wetter D_w of every root and according to this we classify its kind and how it behaves. So the convergence will be affected as we will see in this section.

VII.2.3. Applying the RTO to the ED problem :

In this section the proposed algorithm is applied to solve the economic dispatch problem with valve-point effect. To apply the RTO, the following steps have to be taken.

Step.1. Define the input data

In this step, the input data including the cost coefficients of the generators, output generator constraints, transmission loss matrix coefficients and loads, the number of iterations ($Iter_{max}$), the size of the population (candidates), the adjustable parameters c_1, c_2 and c_3 and the difference rates R_n, R_r and R_c.

Step.2. Generate the initial population.

Initialize randomly the individuals of the population according to the limit of each unit including individual dimensions. These initial individuals must be feasible candidate solutions that satisfy the practical operation constraints.

Step.3. To each individual P_{Gi} of the population, employ the β-coefficient loss formula to calculate the transmission loss P_L.

Step.4. Calculate the evaluation value (fitness) of each individual P_{Gi} in the population using the evaluation function given by (II.16), (Evaluate *fitness* $D_{W\,i}$ for each candidate).

Step.5. Compare each individual's evaluation value with it's Pg^{lbest} is the best fitness of the particle up.

Step.6. Calculate new candidates using (VII.1), (VII.2) and (VII.3).

$$P_{Gi,d}(k+1) = P_{Gr,d}(k) + c_3 + D_{Wi} \times randn \times \left|P_{Gd,Max} - P_{Gd,Min}\right| / it, \quad \text{for i} = 1 \text{ to } \mathrm{R_r} \times \mathrm{n}$$
$$P_{Gi,d}(k+1) = P_{Gd}^{best}(k) + c_1 + D_{Wi} \times randn \times \left|P_{Gd,Max} - P_{Gd,Min}\right| / (n \times it), \quad \text{for i} = \mathrm{R_r} \times \mathrm{n} + 1 \text{ to} (\mathrm{R_r} + \mathrm{R_n}) \times \mathrm{n}$$
$$P_{Gi,d}(k+1) = P_{Gi,d}(k) + c_2 + D_{Wi} \times rand \times \left|P_{Gd}^{best}(k) - P_{Gi,d}(k)\right|, \quad \text{for i} = (1 - \mathrm{R_c}) \times \mathrm{n} \text{ to n}$$

(VII.5)

Where *d=1, 2,…, m* and $P_{Gr,d}(k)$ is individual selected randomly from the current population;

Where n is the population size, m is the number of units, $P_{Gd,Max}$ and $P_{Gd,Min}$ are parameter upper and lower limits and k number of iterations.

Step.7. If the number of iterations reaches the maximum, then go to Step 8. Otherwise, go to Step 3.

Step.8. The individual that generates the latest Pg^{best} is the optimal generation power of each unit with the minimum total generation cost.

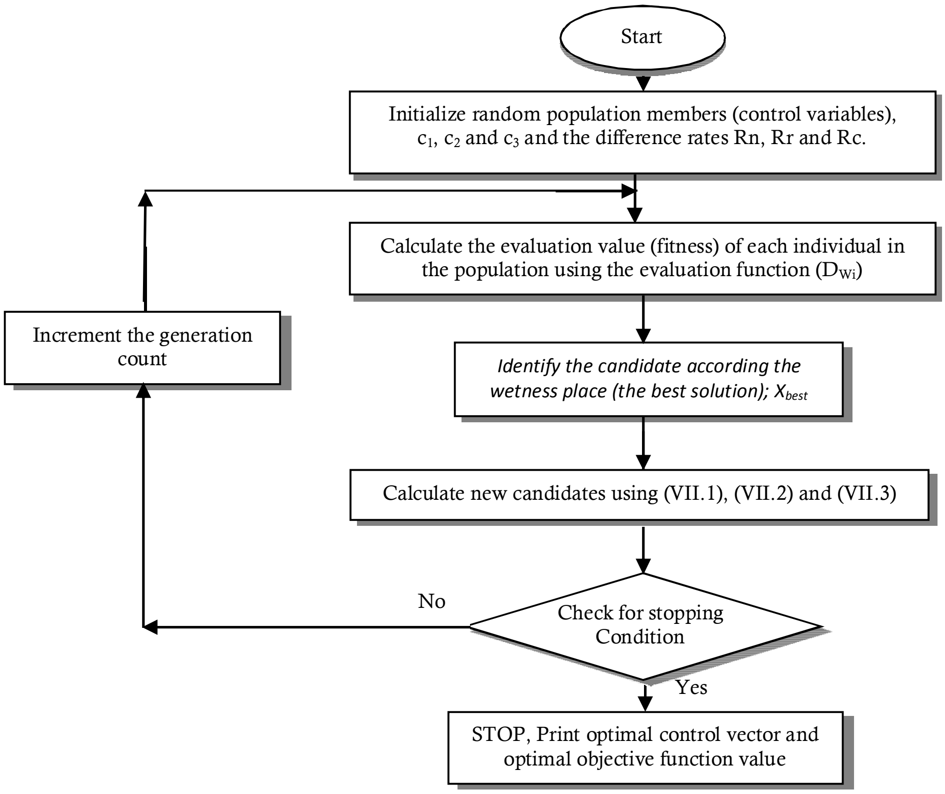


Figure VII.5 : *Flowchart of the proposed RTO algorithm.*

Fig. VII.5 depicts the schematic representation of the proposed algorithm to solve the ED problem.

VII.2.4. Experimental analysis and numerical results :

In order to verify the feasibility and efficiency of the proposed algorithm RTO was tested on two tests the first one, is four different benchmarks problems and the second one are three test cases for solving ED problem with valve-point effects. These are 3, 6 and 13 units systems including valve-point loading.

In these examples, the software was implemented by the MATLAB language, on a Pentium IV, 3-GHz personal computer with 4 GB RAM under Windows XP.

VII.2.4.1. *Validation (benchmark tests):*

Before solving economic dispatch problems, RTO was benchmarked using four numerical examples which are given as follows in detail. The new algorithm RTO has been tested and compared with the RTO_M on the benchmark problems taken from [205]. The difficulty levels of most benchmark functions are adjustable by setting their parameters. From the standard set of benchmark problems available in the literature, four important functions two of which are unimodal (containing only one optimum) and two of which are multimodal (containing many local optima, but only one global optimum) are considered to test the efficacy of the proposed methods [206]. This list comprises some widely used test functions such as sphere, Rosenbrock, Dejong, Griewangk, and Rastrigin functions given in table VII.1 shows the main properties of the selected benchmark functions used in the experiments.

Two criteria are applied to terminate the simulation of the algorithms: reaching maximum number of iterations which is set to a constant number and the second criterion is getting a minimum error.

100 candidates were initialized in regions that include the global optimum for a fair evaluation. The algorithms were run for 100 times to catch their stochastic properties. In this experiment, maximum iteration number was set to 500 and the goal is not to find the global optimum values but to find out the potential of the algorithms. Algorithm success rate defined by; how often does the algorithm get the exactitude before it completes the number of the whole iterations or all 100 trials.

Table VII.1 : Properties of test problems.

Function name	*Definition*	*lower bound*	*upper bound*	*optimum point*	*Property*
Rosenbrock	$\sum_{i=1}^{N-1} 100(x_{i+1} - x_i^2)^2 + (1 - x_i)^2$	-2.048	2.048	0	Unimodal
Dejong	$\sum_{i=1}^{N} x_i^2$	-5.12	5.12	0	Unimodal
Griewangk	$\sum_{i=1}^{N} (x_i^2 / 4000) - \prod_{i=1}^{N} (x_i / \sqrt{i}) + 1$	-50	50	0	Multimodal
Rastrigin	$10 \times N + \sum_{i=1}^{N} (x_i^2 - 10.\cos(2\pi.x_i))$	-5.12	5.12	0	Multimodal

We remark that the positive aspect of the RTO method in comparison with RTOM, is the probability to get the global solution and to avoid falling in the local one as it appears in the table VII.2, all this refers to the stability of the roots number in each kind, so the roots stay as they are when they look for water (their behavior) randomly in same parts of them, (the random orientation when they look for water) integration with the convergence towards the solution according to the previous relations, where they stay on this orientation even the reach the initial solution, that can be a local solution, opposite to RTO_M which all the roots to the solution by gathering around the first most witness points, but this can make negative to get the local solution, but we can find that these roots can get quickly the solution by a less number of iteration than RTO method also more powerful in the unimodal functions as Rosenbrock and Dejong, but the RTO find its power in the multimodal functions as Griewangk and Rastrigin where it's so possible to get the global solution.

Table VII.2 : Success rates of different algorithms.

algorithms	*RTO*					*RTO_M*				
Tolerance	**1e-5**	**1e-5**	**1e-6**	**1e-7**	**1e-8**	**1e-9**	**1e-6**	**1e-7**	**1e-8**	**1e-9**
Rosenbrock (N=10)	100	100	98	98	96	96	98	98	97	87
Rosenbrock (N=5)	100	100	100	100	100	100	100	100	100	99
Rosenbrock (N=3)	100	100	100	100	100	100	100	100	100	100
Dejong (N=10)	100	100	100	100	100	100	100	100	100	100
Dejong (N=3)	100	100	100	100	100	100	100	100	100	100
Griewangk (N=10)	100	100	100	100	100	100	100	100	100	100
Griewangk (N=5)	100	100	100	100	100	100	100	100	100	100
Rastrigin (N=2)	77	58	51	45	40	37	75	72	68	65

Table VII.3 : Success rates of RTO algorithms using different rates parameters; R_n, R_r and R_c.

	Rosenbrock (N=10)		*Dejong (N=10)*		*Griewangk (N=10)*		*Rastrigin (N=2)*	
Tolerance	**1e-5**	**1e-7**	**1e-5**	**1e-7**	**1e-5**	**1e-7**	**1e-5**	**1e-7**
R_n=1.0, R_r=0.0 and R_c=0.0	0	0	0	0	0	0	2	0
R_n=0.7, R_r=0.3 and R_c=0.0	99	24	100	100	24	0	67	62
R_n=0.6, R_r=0.4 and R_c=0.0	99	18	100	100	20	0	77	70
R_n=0.3, R_r=0.7 and R_c=0.0	98	11	100	80	30	0	98	98
R_n=0.0, R_r=1.0 and R_c=0.0	16	0	0	0	0	0	0	0
R_n=0.9, R_r=0.0 and R_c=0.1	0	0	0	0	0	0	6	4
R_n=0.6, R_r=0.3 and R_c=0.1	100	33	100	100	94	88	66	59
R_n=0.3, R_r=0.6 and R_c=0.1	100	37	100	100	94	88	95	92
R_n=0.1, R_r=0.8 and R_c=0.1	100	77	100	100	96	90	98	96
R_n=0.0, R_r=0.9 and R_c=0.1	11	0	100	98	96	93	88	35
R_n=0.7, R_r=0.0 and R_c=0.3	19	9	2	0	100	99	25	19
R_n=0.4, R_r=0.3 and R_c=0.3	100	98	100	100	100	100	77	72
R_n=0.3, R_r=0.4 and R_c=0.3	100	97	100	100	100	100	74	70
R_n=0.0, R_r=0.7 and R_c=0.3	56	27	100	100	100	100	100	70
R_n=0.4, R_r=0.0 and R_c=0.6	93	88	0	0	100	100	32	25
R_n=0.1, R_r=0.0 and R_c=0.9	98	92	80	74	100	100	55	52
R_n=0.0, R_r=0.1 and R_c=0.9	100	99	100	99	100	100	85	84
R_n=0.0, R_r=0.0 and R_c=1.0	100	97	100	98	100	99	62	59

The table VII.3 presents the effect of the difference of this rate values R_n, R_r and R_c at the convergence to the solution with the different functions and the different exactitude, this table clarify the desired rates (by an experiment) that should be taken to get exactly the solution according to the kind of problem, it's too important to see that the selected rates in the table VII.2 according to this table through the possibility to get the global solution and the number of iterations, there is a relation between them when the rate of getting solution increase this means that the speed of convergence is so good (the number of iterations is few).

Table VII.4 : comparison of Success rates between different algorithms.

	BB–BC [206]		BB–CBC [206]		UBB–BC [206]		UBB–CBC [206]		RTO		RTO_M	
Tolerance	**1e-5**	**1e-6**	**1e-5**	**1e-6**	**1e-5**	**1e-5**	**1e-6**	**1e-6**	**1e-5**	**1e-6**	**1e-5**	**1e-6**
Rosenbrock (N=100)	100	69	100	100	100	92	82	100	100	100	95	93
Dejong (N= 3)	100	31	100	70	100	100	100	61	100	78	100	100
Griewangk (N=2)	23	19	31	30	36	100	100	31	39	38	100	99
Rastrigin (N=2)	30	26	80	75	84	29	22	79	90	86	73	67

In order to make a fair comparison between our proposed algorithm RTO with other heuristic methods [206], 500 iterations are chosen as stopping criteria in the simulations and the population size is kept fixed as 40 in the example and the benchmark tests.

Table VII.4 represents the success rates obtained from RTO, RTO_M, BB–BC (Big Bang–Big Crunch), BB–CBC (Big Bang–Chaotic Big Crunch optimization), UBB–BC (Uniform Big Bang–Big Crunch), and UBB–CBC (Uniform Big Bang–Chaotic Big Crunch algorithms) at different quality levels for the benchmark functions.

VII.2.4.2. *Economic dispatch problems :*

A. *Test system 1: small system (3-unit system) :*

This test case study considering three thermal units of generation with effects of valve-point is given in appendix. 4 (table A. 4). In this case, the load demand expected to be determined was P_D= 850 MW.

The simulation parameters for the proposed algorithm are :

- The number of generation is 50 iterations and Size of population 100 individuals (candidates).

- Take the difference rate values R_n=0.4, R_r=0.3 and R_c=0.3.

R_n, R_r and R_c are adjustable parameters controlling the influence of the convergence properties of the proposed algorithm.

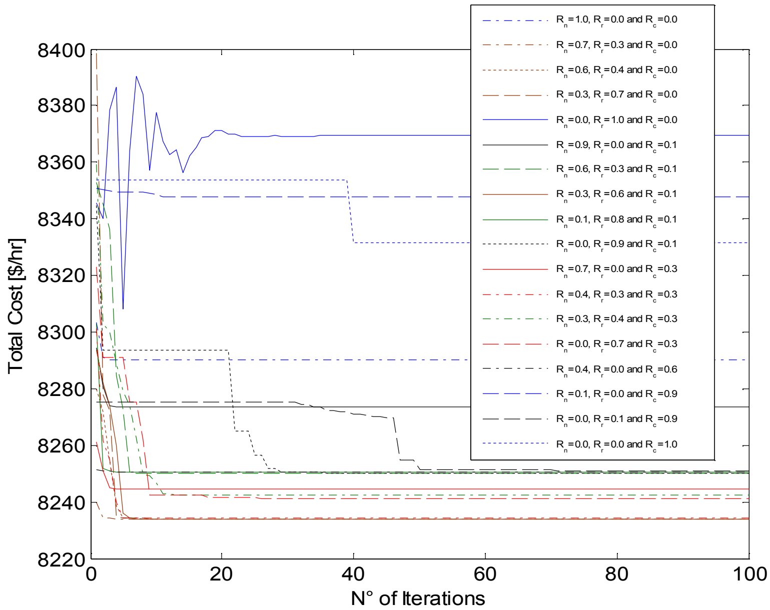


Figure VII.6 : *The convergence characteristic of the three-generator systems for different adjustable parameters to the RTO algorithms.*

Fig. VII.6 shows the effect of various values for R_n, R_r and R_c on the convergence characteristic of the proposed method for three-generating unit system. This figure shows that R_n=0.4, R_r=0.3 and R_c=0.3, are suitable values for RTO algorithm. These parameter values are used for all other examples presented.

For this problem, we can make the appropriate choice of the adjustable parameters codified somewhat, resulting from experimental and observational limits.

The results obtained for this case study are listed in table VII.5 the proposed algorithm has obtained the optimal solution values for the 3 units test system by completing 100 iterations in 0.3008 s, which shows that the RTO algorithm has approximately good solution for the power demand of 850 MW. The best fuel cost result obtained from the proposed RTO algorithm and other optimization algorithms are compared in table VII.6. From table VII.6 it is seen clearly that the PS approach did not meet the load demand.

Table VII.5 : Results obtained by proposed method for test system 1.

Units (MW)	Proposed RTO
1	300.2536
2	149.7485
3	399.9972
Total Power Output(MW)	850.000
Total Cost ($/h)	**8234.07157**
time (sec)	0.3008

Table VII.6 : Comparison of proposed method for test system 1.

Method	P_1(MW)	P_2(MW)	P_3(MW)	P_D(MW)	Cost ($/h)
GA [87]	398.700	50.100	399.600	848.400	8222.07
EP [87]	300.264	149.736	400.000	850.000	8234.07
EP-SQP [87]	300.267	149.733	400.000	850.000	8234.07
PSO [87]	300.268	149.732	400.000	850.000	8234.07
PSO-SQP [87]	300.267	149.733	400.000	850.000	8234.07
MPSO [207]	300.27	149.74	400.00	850.000	8234.07
PS [136]	300.2663	149.7331	399.9996	849.9990	8234.05
GSA [137]	300.2102	149.7953	399.9958	850.0013	8234.1
Proposed RTO	300.2669	149.7331	400.0000	850.0000	**8234.0717**

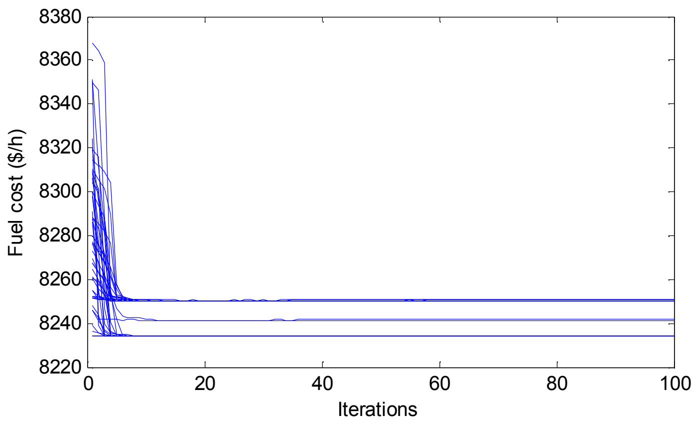


Figure VII.7 : *Convergence of fitness value for load demand 850 MW.*

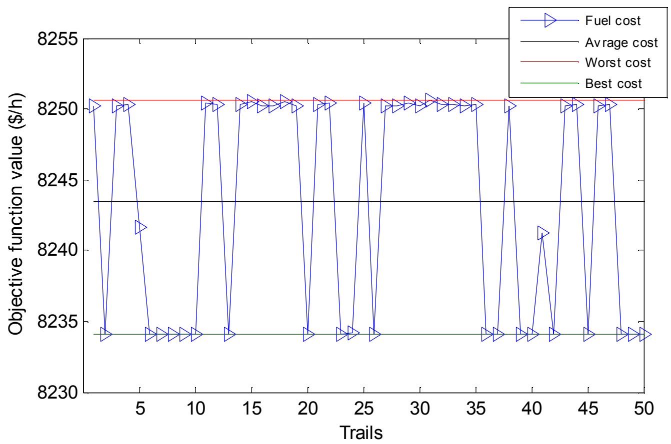


Figure VII.8 : *Distribution of objective function value for 50 Trails.*

A convergence characteristic of the RTO algorithm for the three generator systems shown in figs. VII.7 and VII.8 shows the distribution of the generation cost of the best solution for each run in the test system of 3 units.

B. *Test System 2: IEEE 30 buses system (6-unit):*

The second test system is a 6-unit system. System (IEEE 30 buses system*)* with effects of valve-point. The required load demands to be met by all the 6 generating units are 283.4 MW. The data for this system is provided in [8], [25] as given appendix. 1 (tables A.1 and A.2). In this test system, the transmission losses are considered and the loss coefficients β matrices are shown in appendix.

The setup for the proposed algorithm is executed with following parameters:

- The number of generation is 50 iterations and Size of population 100 individuals (candidates).

Table VII.7 shows the obtained results for this system. Results of the proposed method RTO are in bold. Minimum cost, Mean cost and maximum cost over the 50 trial runs are compared with the results of combination of modified subgradient MSG and harmony search HS algorithms (MSG-HP) [29], PSO [29], the Newton's second order approach NSOA [28], combines the genetic algorithm GA with active power optimization APO (GA-APO) [28] and genetic algorithm GA [28] in table VII.8.

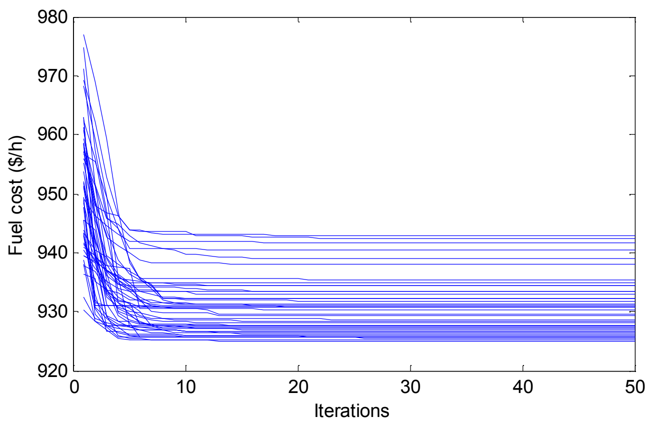


Figure VII. 9 : *Convergence of fitness value with valve-point effects.*

Table VII.7 : Results obtained by proposed method for test system 2.

	Solution methods					
	GA [208]	GA-APO [208]	NSOA [208]	PSO [209]	MSG-HP [209]	RTO
$P_{G,1}$	150.724	133.9816	182.478	197.8648	199.6331	199.5996
$P_{G,2}$	60.8707	37.2158	48.3525	50.3374	20.0000	20.0008
$P_{G,5}$	30.8965	37.7677	19.8553	15.0000	23.7624	24.1658
$P_{G,8}$	14.2138	28.3492	17.1370	10.0000	18.3934	17.7409
$P_{G,11}$	19.4888	18.7929	13.6677	10.0000	17.1018	19.0252
$P_{G,13}$	15.9154	38.0525	12.3487	12.0000	15.6922	13.7428
$P_{G,Total}$(MW)	292.1096	294.1600	293.8395	295.2022	294.5829	294.2754
F_{total} (R/h)	996.0369	1101.491	984.9365	925.7581	925.6406	**924.9724**
P_{loss}	8.7060	10.7563	10.4395	11.8022	11.1830	10.8754
Time (s)	0.5780	0.156	0.0150	0.3529	0.6215	0.3771

Table VII.8 : Comparison of results (test system 2) in the 50 trial tests.

		Solution methods					
		RTO	MSG-HP [209]	PSO [209]	NSOA [208]	GA-APO [208]	GA [208]
Min	F_{total} (R/h)	**924.9724**	925.641	925.758	984.94	996.04	996.04
	Time (s)	0.3771	0.62151	0.35290	0.0150	0.156	0.141
Max	F_{total} (R/h)	943.8712	928.599	928.427	992.48	1101.49	1117.13
	Time (s)	0.3827	0.77132	0.35591	0.0310	0.578	0.5780
Mean	F_{total} (R/h)	930.17814	926.851	926.388	NA	NA	NA
	Time (s)	0.3785	0.72484	0.35749	NA	NA	NA

NA denotes that the value was not available in the literature.

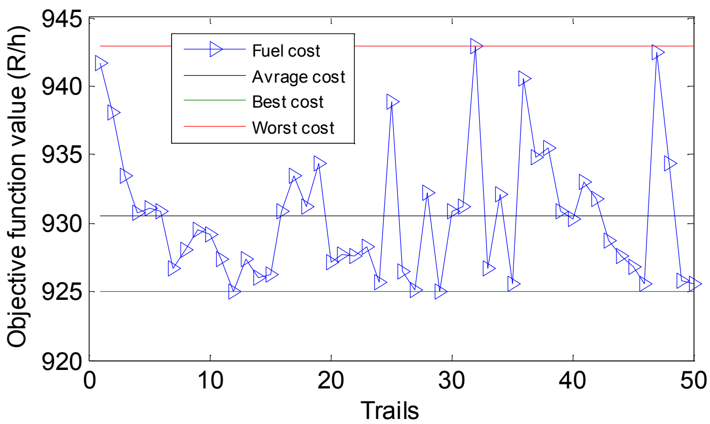


Figure VII. 10 : *Distribution of objective function value for 30 Trails.*

When the adjustable parameters is selected, optimal solution values for the IEEE 30 buses test system are obtained as 199.5996, 20.0008, 24.1658, 17.7409, 19.0252 and 13.7428. The proposed algorithm has found the optimal solution values for the test system by completing 50 iterations in 0.3771 s. It is observed, through the table VII.7, that the RTO algorithm achieves much better optimal solution values when compared to the results in the literature. In other words, the RTO algorithm is 59.9641 R/h better when compared to the NSOA with the best solution value in the literature [28], also is 0.6682 R/h better then MSG-HP algorithm. In fig. VII.9 show that convergence characteristic curve of the best case with valve point effect, the fig. VII.10 shows distribution the generation cost of the best solution value for 30 trails in the test system.

C. *Test System 3: 13-unit system :*

This test system is a 13-generator system with valve-point loading effect. The coefficients of fuel cost functions as given appendix. 4 (table A.8) [8], [25]. The ED problem is solved for two different load levels (PD= 1800 MW and PD= 2500 MW). This test system has many local optima and no global solution has been reported yet. The population size and maximum iteration number are fixed to 200 and 100, respectively.

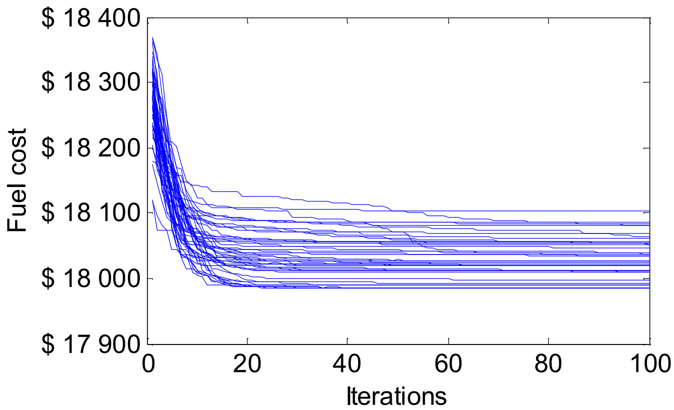


Figure VII.11 : *Convergence of fitness value for load demand 1800 MW.*

The obtained result for load demand equal to 1800 MW is presented in table VII.9. Results of the proposed method are in bold. The results are compared in terms of minimum cost, mean cost, and maximum cost over 50 runs with the results of hybrid multi-agent based PSO (HMAPSO) [30], modified differential evolution algorithm (MDE) [31], self-tuning hybrid differential evolution algorithm (SHDE) [32], pattern search method (PSM) [35], hybrid genetic algorithm (HGA) [36], quantum-inspired PSO (QPSO) [33], PSO [30] and PSO with time varying acceleration coefficients (PSO-TVAC) [34]. The results of the aforementioned methods that presented in table VII.10, have been directly quoted from their respective references. Convergence characteristic of the RTO for 13-generator test case with load demand of 1800 MW is depicted in fig. VII.11. Fig. VII.12 shows distribution the generation cost of the best solution for each run in the test System 3.

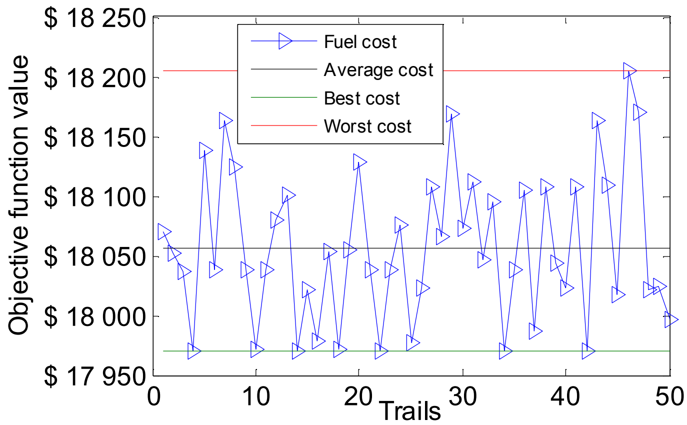


Figure VII.12 : *Distribution of objective function value for 30 Trails (1800 MW).*

Table VII.9 : Comparison of simulation results for test system 3 (case I, load = 1800 MW).

Unit	HMAPSO [210]	MDE [211]	SHDE [214]	PSM [214]	HGA [142]	QPSO [212]	PSO [210]	PSO-TVAC [213]	Proposed
1	538.5611	628.318	628.3172	538.5587	628.3185	538.56	538.561	628.319	628.3072
2	224.4831	149.594	149.5986	224.6416	222.7491	224.7	299.355	149.597	224.3420
3	150.0622	222.758	222.7987	149.8468	149.5996	150.09	75.037	222.749	297.7060
4	109.8862	109.865	109.8673	109.8666	109.8665	109.87	159.734	109.867	60.0000
5	109.9902	109.864	109.8418	109.8666	109.8665	109.87	60.078	109.867	109.8529
6	109.8666	109.866	60	109.8666	109.8665	109.87	109.864	109.867	60.0000
7	109.9903	109.865	109.8641	109.8666	109.8665	109.87	109.913	109.867	60.0000
8	109.8688	60	109.8547	109.8666	60	159.753	109.87	109.867	109.7956
9	109.8668	109.866	109.8576	109.8666	109.8665	109.87	60.069	60	60.0002
10	40	40	40	77.4666	40	77.41	40.035	40	40.0000
11	77.4247	40	40	40.2166	40	40	77.561	40	40.0000
12	55	55	55	55.0347	55	55.01	55.042	55	55.0000
13	55	55	55	55.0347	55	55.01	55	55	55.0000
$P_{G,Total}$	1800	1799.996	1800	1799.9993	1799.9997	1800.002	1800	1800	1800.0044
Min cost	17969.31	17960.39	17963.89	17969.17	17963.83	17969.01	18014.16	17963.879	**17969.8024**
Mean cost	17969.31	17967.19	18046.38	18088.84	17988.04	18075.11	18104.65	18154.562	18056.9358
Max cost	17969.31	17969.09	NA	18233.52	NA	NA	18249.89	18358.31	18204.6303

NA denotes that the value was not available in the literature.

Also, simulation is done for power demand of 2520 MW. The obtained results are presented in table VII.11 and compared with the results of hybrid genetic algorithm (HGA) [36], differential evolution (DE) [21], FAPSO-VDE [39], improved coordinated aggregation based PSO (ICA-PSO) algorithm [40] and Iteration PSO (IPSO) [41]. The minimum, average and maximum costs presented in table VII.11 are obtained over the 50 trial runs. Results of the proposed method are in bold. It can be observed from table VII.11 that the proposed technique provided almost significantly better results in comparison with the previously developed techniques.

Table VII.10: Comparison of proposed method for test system 3 (case I, 1800 MW).

Method	Total Cost ($/h)	Method	Total Cost ($/h)
PSO [219]	18030.72	IGA_MU [89]	17963.98
EP-SQP [87]	17991.03	ST-HDE [214]	17963.89
HDE [214]	17975.73	HGA [221]	17963.83
CGA-MU [89]	17975.34	HQPSO(5)	17963.9571
PSO-SQP [87]	17969.93	[138]	17963.83
PS [136]	17969.17	DE [143]	17960.3684
UHGA [220]	17964.81	GSA [137]	**17969.8024**
QPSO [141]	17964	Proposed RTO	

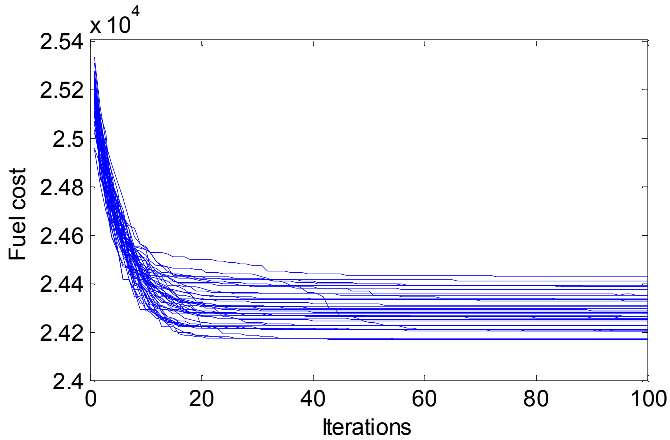


Figure VII.13 : *Convergence of fitness value for load demand 2520 MW.*

The convergence behavior of the proposed RTO for power demand of 2520 MW is depicted in fig. VII.13. Fig. VII.14 shows distribution the generation cost of the best solution for each run in the test System 3. The best fuel cost result obtained from proposed RTO and other optimization algorithms are compared in tables VII.10 and VII.13 for load demand 1800 and 2520 MW respectively.

Table VII.11: Comparison of simulation results for test system 3 (case II , load = 2520 MW).

Unit	HGA [142]	DE [215]	FAPSO-VDE [216]	ICA-PSO [217]	IPSO [218]	RTO
1	628.3184	628.3185	628.3185	628.32	628.319	628.2518
2	299.1992	299.1993	299.1993	299.19	299.199	299.1535
3	299.1988	299.1993	299.1993	294.51	295.878	296.1073
4	159.733	159.7331	159.7331	159.73	159.265	159.6753
5	159.7329	159.7331	159.7331	159.73	159.733	159.7332
6	159.7324	159.7331	159.7331	159.73	159.733	159.6176
7	159.733	159.7331	159.7331	159.73	159.733	159.5445
8	159.733	159.7331	159.7331	159.73	159.733	159.6311
9	159.7331	159.7331	159.7331	159.73	159.733	159.4948
10	77.3994	77.3999	77.3999	114.8	77.363	77.1423
11	77.3996	77.3999	77.3999	77.4	77.397	77.3767
12	87.6879	92.3999	87.6845	55	92.397	92.2554
13	92.3992	87.6845	92.3999	92.4	91.517	92.0241
$P_{G,Total}$	2519.9999	2519.9999	2519.9999	2520.0000	2520.0000	2520.0082
Min cost	24169.9177	24169.9177	24169.9176	24168.910	24166.8	**24167.7042**
Mean cost	NA	NA	24169.9176	24175.34	24167.37	24273.5221
Max cost	NA	NA	24169.9176	24184.92	24169.41	24428.1236

NA denotes that the value was not available in the literature.

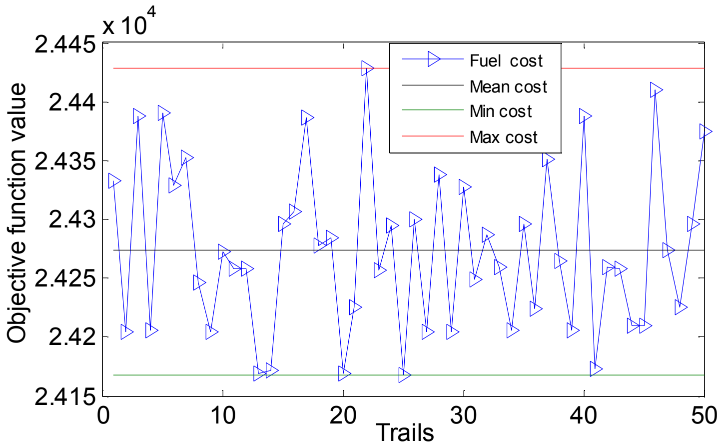


Figure VII.14 : *Distribution of objective function value for 30 Trails (2520 MW).*

Table VII.13 : Comparison of proposed method for test system 3 (case II , load = 2520 MW).

Method	Total Cost ($/h)	Method	Total Cost ($/h)
SA[87]	24970.91	GA-MU [144]	24170.755
GA [87]	24398.23	IGAMU [144]	24169.979
GA-SA[87]	24275.71	HGA [221]	24169.92
EP-SQP [87]	24266.44	DE [216]	24169.9177
PSO-SQP[87]	24261.05	GSA [137]	24164.251357
UHGA [220]	24172.25	Proposed	**24167.7042**

Economic Load dispatch problem with valve-point effects being attempted using RTO algorithm for various generator test system evaluates the performance of the proposed approach.

A numerical simulation including comparative studies has been presented to demonstrate the performance and applicability of the proposed method. The simulation results reveal the superiority of the proposed technique in solving the DE problem with valve point effects. Therefore this approach could also be extended to other optimization and control problems of power systems.

VII.3. GA based Genetic Engineering operation for solving UCP :

The objective of the UCP is to minimize operation-cost while satisfying the constraints. However, power system operation needs reformulate tasks that reflect the changes due to the deregulated power systems to determine generation scheduling from a standpoint of maximizing profit under competitive environment. It is hard to solve due to the complexity [65]. In this section, a new GA operation is introduced, this new operation represents a another kind of crossover its idea derived from genetic engineering (modification), aim is to plant the good genes in a children generation, where we import these good genes from many parents with good qualities resulting from the crossing operation (elite only) for just one child. The purpose of this genetic engineering (GE) operation is to exploit the maximum best characteristics from the elite group in each generation,

We present an extension to the standard genetic algorithm (GA), which is based on concepts of genetic engineering. The motivation is to discover useful and harmful genetic materials and then execute an evolutionary process in such a way that the population becomes increasingly composed of useful genetic material and increasingly free of the harmful genetic material [222]. Compared to the standard GA, it provides some solution quality advantages to our problem.

In this section, a GA based Genetic Engineering operation (GAGE) is proposed to solve the UC problem. The results obtained show that, with the application of the proposed method (GAGE) to the unit commitment problem, better convergences and solutions are obtained than with the application of conventional genetic algorithm and the algorithms proposed the most-recent literature

VII.3.1. Introduction :

Genetic algorithms (GAs) are a family of general stochastic search methods, which can be viewed as computational models of Darwinian evolution theory. They use the analogs of evolutionary operators on a population of states in a search space to find those states that optimize a fitness function. The search space consists of character-strings of fixed or variable length (chromosomes or genotypes) composed of the elements of a given alphabet (alleles). The genotype space is mapped onto another (phenotype) search space. The fitness function is defined as a function of a state in the phenotype space [222].

Since the biological metaphors (genetic representations, neo-Darwinian evolution theory) provide the conceptual basis of GAs, it seems natural to introduce some of the concepts of the most modern branch of biology –genetic engineering– into genetic algorithms [222].

In genetic engineering, recombination can also refer to artificial and deliberate recombination of disparate pieces of chromosome (DNA), often from different organisms, creating what is called recombinant chromosome. A prime example of such a use of genetic recombination is gene targeting, which can be used to add, delete or otherwise change an organism's genes. This technique is important to biomedical researchers as it allows them to study the effects of specific genes. Techniques based on genetic recombination are also applied in protein engineering to develop new proteins of biological interest.

The primary motivation of this work is to identify and use any superior genetic material explicitly by means of genetic engineering. It is similar to the practice of genetic engineering in the genetics of natural organisms. In genetic engineering, the genetic engineer classifies the population into one group that possesses a high level of the property of interest or into another group that lacks it. We shall call the first group "elite". Then the genetic engineer tries to single out the groups of genes (we shall call them the elite genes) in the genotypes that are hypothesized to be responsible for the properties of interest. we attempt to produce the next population whose genetic material contains more of these useful elite genes [222].

This concept is inspired by the practice of genetic engineering in the genetics of natural organisms. We will refer to techniques that manipulate genetic material methods as genetic engineering operators.

VII.3.2. Modified Genetic Algorithm (GAGE) :

The GA is modified to include additional genetic engineering operation. The modified GA includes cycles where new elite genes are evolved, and a new population that is richer in superior genes is generated [222].

A library of the descriptions of currently identified elite genes are maintained. As the evolution process proceeds, enhanced by the inclusion of the genetic analysis and the genetic engineering operators, new elite genes are identified and added to this library. The elite genes that have been incorporated into this library earlier are retested against the newly generated populations. This involves checking that they are still superior elite genes for the current population. Those that do not pass this testing are deleted from the library [222].

The suggested GAGE models this simple picture of Darwinian evolution enhanced by genetic engineering technology. For each generation, the comparisons of genetic material of the most fit subpopulations are carried out. This yields current knowledge about the useful and harmful genetic features. This knowledge is then used to genetically engineer the current population during a pre-reproduction stage [222].

The GAGE has the following general structure [222]:

1. Initialization of the population (randomly) and a library of elite genes – the superior genes.
2. (a) Extraction of the super (highly fit) groups of individuals from the current population.

   (b) Identification of the superior elite genes that distinguish this group from other at the genetic level. For example, this could be the most fit 10% of the population.

   (c)Updating the elite genes' library by adding the newly evolved genes and eliminating the ones that test negatively.

(d) Pre-reproduction processing step that includes various direct manipulations of genotypes of the population. The goal here is to produce superior genes in the genetic pool.

3. Reproduction.
4. If the stop conditions (for example, the given number of generations has been produced or the population has converged, etc.) are not met, go to step 1.

Note that steps 1 and 2 of the algorithm may be executed after a fixed number of generations at predefined intervals.

We will try to introduce a set of genes derived from a specific set of generation -with the best qualities- and who are in our case they are an elite group, and will be the number of genes input to the host randomly and will be the placement of these gene also randomly, the choice between the genes that represent the same role with the same who's in the genes of an elite group will be the most frequent choice of any dominant quality.

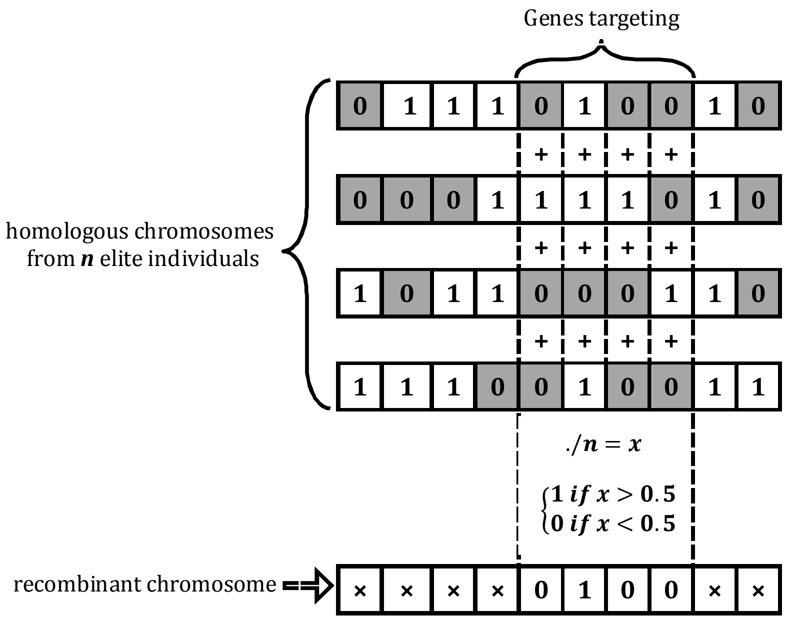


Figure VII.14 : *genetic engineering strategy to create recombinant chromosome by genes targeting.*

Will be the method of determining the dominant gene in the search algorithm for the most frequent as default, and may be a random sorting as a second way,

In fig. VII.14 provide an example of how the dominant genes transmission from a candidate of the elite group to genes of the children , where we transferred the dominant genes from four members randomly selected of the elite, by identifying the part of the chromosome to be transferred (by two points), the gene in host individual will be as the following :

$$gene_{Targeting} = \begin{cases} 1 \text{ if } x \rangle 0.5 \\ 0 \text{ if } x \langle 0.5 \end{cases}, \text{ where } x = \frac{gene_1(0 or 1) + gene_2(0 or 1) + gene_3(0 or 1) + gene_4(0 or 1)}{4} \quad \text{(VII.6)}$$

From the previous relation we notice that there is a part of the domain, which is not defined when $x = 0.5$ in this case, we will resort to random choice between the 0 or 1, and this is the last stage to be applied on the output of the previous generation mechanisms by a predetermined probability P_E (probability of engineering).

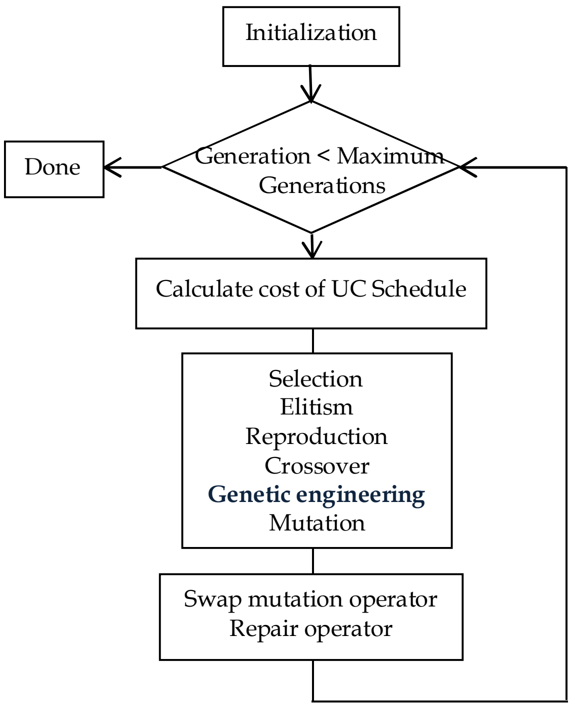


Figure VII.15 : *GAGE flowchart.*

VII.3.3. Simulation results :

In this section efficiency of the proposed method GAGE has been tested by solving some standard and Algeria test system UC problems. However a very widely used ten-unit system has been the only standard UC problem solved in many papers, variety of problems have been chosen to solve using the proposed method to yield a good perception of its capabilities. These standard problems are a ten-unit system, twenty-unit system, forty-unit system, sixty-unit systems and Algeria test system.

Total cost of various methods including the proposed method have been compared in three worst, average and best columns which have been achieved from several runs.
The simulation results have been yield using Matlab® software, and the computer in which the simulations have been done has a Pentium IV, 3-GHz computer with 4 GB RAM.

VII.3.3.1. ***Test system 1: standard test :***
The proposed RCGA is initially tested on a simple ten-unit base system with a 24-h time horizon. The unit characteristics of the ten-unit system and the demand are given in Appendix. 6 (A .11 and A.12, respectively).

Case 1. A system with ten generating units with 10% of spinning reserve has been selected to study in this part. According to the table VII.15, the UC-GAGE surpasses other methods in the Best column. One of the widely-used criterions in qualifying UC methods has been the mean value of their solutions over several executions which indicates the robustness of those methods. According to this norm, the small average amount of the PUC- GAGE is a measure of its robustness in producing similar and high quality solutions over ten independent executions. Another noteworthy data in this table is successful rate of the solutions produced by the UC part without any modification.

Table VII.14 shows the best combination of scheduled-units in the initial population. The total generation cost through the scheduling duration is $563,937.6874. Table VII.14 shows the simulation results including the production cost, transition cost, and spinning reserve capacity of each scheduling time interval, unit-scheduled for 24-hour duration and the total generation cost. The total generation cost of the best combination of scheduled-units is $563,937.6874. Fig. VII.16 shows the convergence tendency of the best evaluation value in the population during GAGE processing with RCGA and the conventional GA.

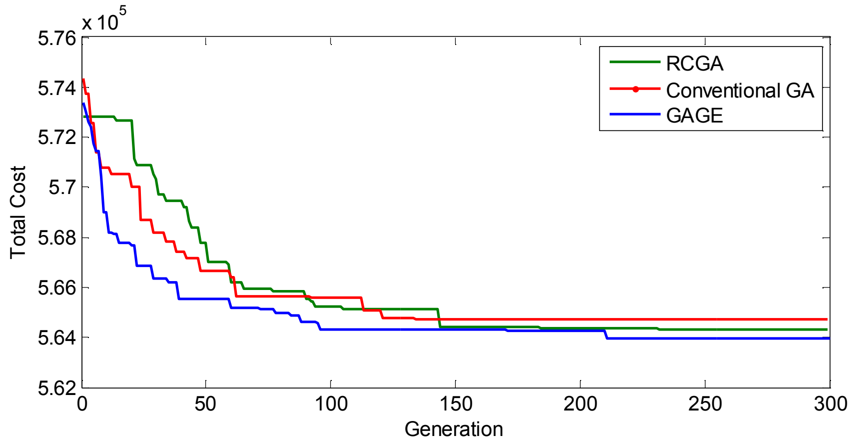


Figure VII.16 : *Typical performance of the GAGE versus RCGA and Conventional GA.*

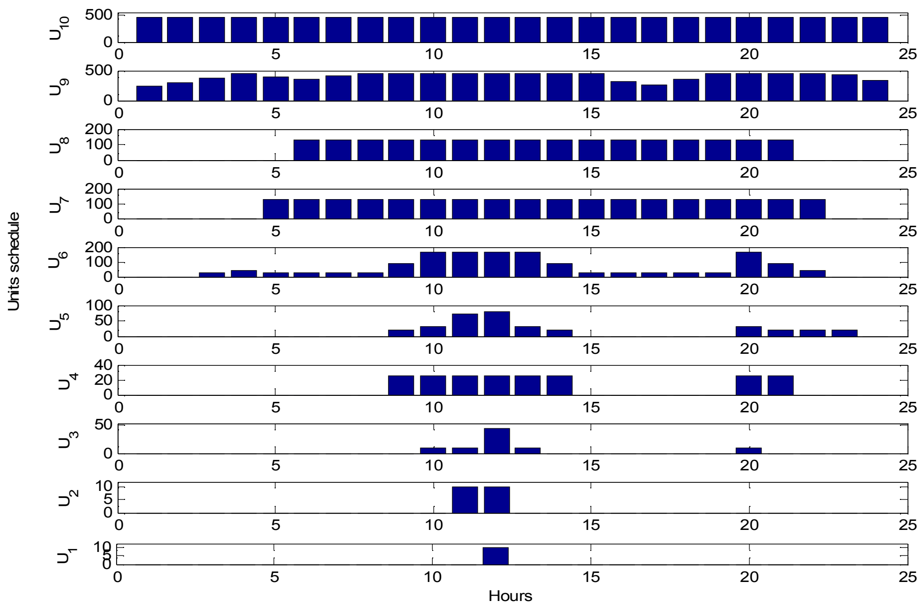


Figure VI.17 : *The output data for all 10 units.*

Fig. VII.17 shows the results of unit commitment optimization problem for ten-unit system by the proposed GAGE with a 24-h time horizon.

To show the advantages of the proposed method, we will compare the performance of the proposal method GAGE with the various methods of the most recent literature as a Methodological priority list, a binary-real-coded genetic algorithm, enhanced simulated annealing algorithm, advanced quantum-inspired evolutionary algorithm, Muller method, advanced fuzzy controlled binary particle swarm optimization and real coded firefly tighter relaxation algorithm in table VI.15.

Table VII.14 : Best individual-Generation schedule and costs obtained by GA for 10 unit system with 10% of spinning reserve.

Hour	Unit Schedule	Production Cost ($)	Transition Cost ($)	Spinning Reserve [MW]	Generation schedule (MW)									
					$Unit_1$	$Unit_2$	$Unit_3$	$Unit_4$	$Unit_5$	$Unit_6$	$Unit_7$	$Unit_8$	$Unit_9$	$Unit_{10}$
1	1100000000	13683.1297	0	210	**455**	**245**	0	0	0	0	0	0	0	0
2	1100000000	14554.4997	0	160	**455**	**295**	0	0	0	0	0	0	0	0
3	1100100000	16809.4485	900	222	**455**	**370**	0	0	**25**	0	0	0	0	0
4	1100100000	18597.6677	0	122	**455**	**455**	0	0	**40**	0	0	0	0	0
5	1101100000	20020.0195	560	202	**455**	**390**	0	**130**	**25**	0	0	0	0	0
6	1111100000	22387.0445	1100	232	**455**	**360**	**130**	**130**	**25**	0	0	0	0	0
7	1111100000	23261.9795	0	182	**455**	**410**	**130**	**130**	**25**	0	0	0	0	0
8	1111100000	24150.3407	0	132	**455**	**455**	**130**	**130**	**30**	0	0	0	0	0
9	1111111000	27251.0560	860	197	**455**	**455**	**130**	**130**	**85**	**20**	**25**	0	0	0
10	1111111100	30057.5503	60	152	**455**	**455**	**130**	**130**	**162**	**33**	**25**	**10**	0	0
11	1111111110	31916.0611	60	157	**455**	**455**	**130**	**130**	**162**	**73**	**25**	**10**	**10**	0
12	1111111111	33890.1629	60	162	**455**	**455**	**130**	**130**	**162**	**80**	**25**	**43**	**10**	**10**
13	1111111100	30057.5503	0	152	**455**	**455**	**130**	**130**	**162**	**33**	**25**	**10**	0	0
14	1111111000	27251.0560	0	197	**455**	**455**	**130**	**130**	**85**	**20**	**25**	0	0	0
15	1111100000	24150.3407	0	132	**455**	**455**	**130**	**130**	**30**	0	0	0	0	0
16	1111100000	21513.6595	0	282	**455**	**310**	**130**	**130**	**25**	0	0	0	0	0
17	1111100000	20641.8245	0	332	**455**	**260**	**130**	**130**	**25**	0	0	0	0	0
18	1111100000	22387.0445	0	232	**455**	**360**	**130**	**130**	**25**	0	0	0	0	0
19	1111100000	24150.3407	0	132	**455**	**455**	**130**	**130**	**30**	0	0	0	0	0
20	1111111100	30057.5503	490	152	**455**	**455**	**130**	**130**	**162**	**33**	**25**	**10**	0	0
21	1111111000	27251.0560	0	197	**455**	**455**	**130**	**130**	**85**	**20**	**25**	0	0	0
22	1100111000	22735.5210	0	137	**455**	**455**	0	0	**145**	**20**	**25**	0	0	0
23	1100010000	17645.3637	0	90	**455**	**425**	0	0	0	**20**	0	0	0	0
24	1100000000	15427.4197	0	110	**455**	**345**	0	0	0	0	0	0	0	0
Total		**559,847.6874**	**4090**	**4275**	Total generation cost ($):					**563,937.6874**				

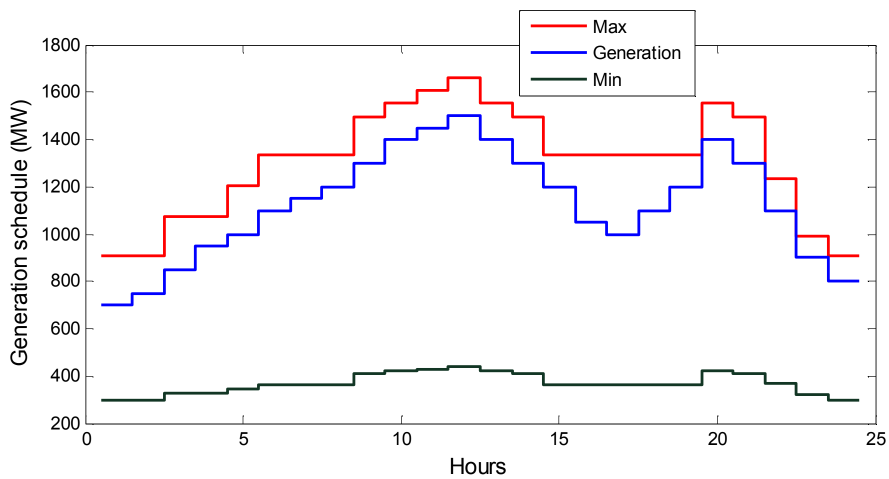


Figure VI.18 : *The output data for Generation schedule and minimum and maximum power.*

From table VI.15, it can be noted that GAGE performs superior to the compared algorithms, in terms of solution quality and CPU times, the GAGE can find the optimal solution with the lowest costs and mean deviation. Fig. VI.18 shows the output data for the generation schedule, minimum and maximum power.

Table VI.15 : Comparison of total cost of the proposed method with recent works for 10-unit system.

Methods	Best cost ($)	Average cost ($)	Worst cost ($)	Standard deviation (%)	Time (sec.)
GA [202]	565,866	567,329	571,336	26 (%)	113
GA [43]	570,781	574,280	576,791	1549.9 ($)	62.29
GA [201]	609,023.69	—	—	—	73.68
SGA [180]	565,121	—	622,846	92.7 (%)	462.31
TLGA [180]	564,426	—	566,182	31 (%)	439.313
FPGA [183]	564,094	566,675	569,237	33 (%)	—
ICGA [184]	566,404	—	—	—	—
EP [189]	—	565,352	—	—	—
GA [58]	565,852	—	570,032	—	—
UCC-GA [201]	563,977	—	565,606	—	—
DP [58]	565,825	—	—	—	—
LR [58]	565,825	—	—	—	—
LRGA [223]	564,800	—	—	—	—
HPSO [62]	563,942.3	564,772.3	565,782.3	—	—
HASP [188]	564,029	564,324	564,490	—	—
ICGA [184]	—	566,404	—	—	—
AG [190]	—	564,005	—	—	—
EALR [60]	563,977	—	—	—	—
CR-GA [193]	—	563,977	—	—	—
MPL [224]	563,977.1	—	—	—	—
TSGB [186]	568,315	—	—	—	—
BCGA [225]	563,938	563,938	564,088	18 (%)	—
PSO [61]	564,212	565,103	565,783	—	—
IPSO [61]	563,954	5564,162	564,579	—	—
SA [226]	565,828	565,988	566,260	3.35(%)	—
QEA–UC [227]	563,938	564,012	564,711	—	—
IQEA–UC [227]	563,938	563,938	563,938	—	—
Muller method [228]	563,977	—	—	51.6(%)	—
BCPSO [229]	563,947	564,285	565,002	5.54(%)	—
BRCFF [230]	563,937	564,772	565,597	—	—
GSA [163]	563,938	564,008	564, 241	2.89(%)	—
RM [231]	563,977	—	—	—	1.15
RCGA	564,338.41	566,997.62	569,637.25	34 (%)	85.12
GAGE	**563,937.68**	566,059.95	567,949.32	29 (%)	93.5

Sign (—) means that no amount has been reported.

Case 2. To verify the effectiveness and efficiency of the proposed RCGA method in solving large-scale UC problem, the proposed method is applied on 20-100 unit systems, the 20, 40 and 60 units data are obtained by duplicating the base case (ten units), whereas the load demands are adjusted in proportion to the system size. In the simulation, the reserve is required to be 10% of the load demand.

For the three UCPs, the best, mean, worst costs and the standard deviations obtained by GAGE are compared with the reported results using SA [226]; GA [58]; EP [189] and the improved PSO (IPSO) [61], improved quantum evolutionary algorithm (IQEA) [232], quantum-inspired binary PSO (QBPSO) [233], DE [234], BNFO [235] and RCGA in 50 trials are summarised in table VI.16.

Table VI.16 : Numerical comparison.

Method	Best cost	Mean cost	Worst cost	Std.dev.cost, %	Mean time, s
20-unit					
GA	1126243	–	1132059	0.52	733
EP	1125494	1127257	1129793	0.38	340
SA	1126251	1127955	1129112	0.25	17
DE	1123988	1124339	1124539	0.05	71
IPSO	1125279	–	1127643	0.21	–
IQEA	1123890	1124320	1124504	0.05	42
QBPSO	1123297	1123981	1124294	0.09	50
BNFO	1123297	1123431	1123563	0.0002	29
RCGA	1125141	1126347	1127654	0.37	264
GAGE	1123389	1124032	1124641	0.32	272
40-unit					
GA	2251911	–	2259706	0.35	2697
EP	2249093	2252612	2256086	0.31	1176
SA	2250063	2252125	2254539	0.20	88
DE	2245631	2245877	2246457	0.04	153
IPSO	2248163	–	2252117	0.18	–
IQEA	2245151	2246026	2246701	0.07	132
QBPSO	2242957	2244657	2245941	0.13	158
BNFO	2242957	2243241	2244237	0.005	92
RCGA	2250286	2251322	2253456	0.35	421
GAGE	2245099	2247634	2248345	0.39	457
60-unit					
GA	3376625	–	3384252	0.23	5840
EP	3371611	3376255	3381012	0.28	–
SA	–	–	3367612	–	2267
DE	3366502	3367166	–	0.03	257
IPSO	3370979	–	3379125	0.24	–
IQEA	3365003	3365667	3366223	0.04	273
QBPSO	3361980	3363763	3365707	0.11	328
BNFO	3361527	3362137	3363251	0.0004	193
RCGA	3370588	3372354	3378214	0.35	756
GAGE	3363154	3364562	3365178	0.30	785

For the 20-, 40-, and 60-Unit systems, in terms of best cost, mean cost and worst cost, GAGE is better than GA, EP, SA, DE, IPSO and IQEA on all the UC problems.

CPU time may reflect the difficulty of algorithm implementations when the number of unit increases. The mean CPU time shown in table VI.16 may not be directly comparable because of different computers used. Therefore it is still substantial to compare GAGE with some recent algorithms [16–19] because of same level of CPU speed (better than Pentium IV). In table VI.16, the CPU times of GAGE are much better than those of other algorithms except SA and DE. Furthermore, it is worth noting that the CPU times of GAGE increase approximately linear with respect to the system size of UCP, which is favourable for large-scale UCP applications.

VII.3.3.1. *Test system 2: the Algerian power network:*

In this case, the proposed method was applied to the electrical network in Algeria (ten-unit) to assess the suitability of the algorithm. The unit characteristics of the Algerian network system and the demand are taken from [236] and also given in Appendix. 8 (A.15 and A.16, respectively). In the simulation, the reserve is required to be 10% of the power demand. Scheduling of the generation obtained by the proposed GA method for the system is given in table VII.17.

Fig. VI.19 shows the convergence tendency of the best evaluation value in the population during GAGE processing.

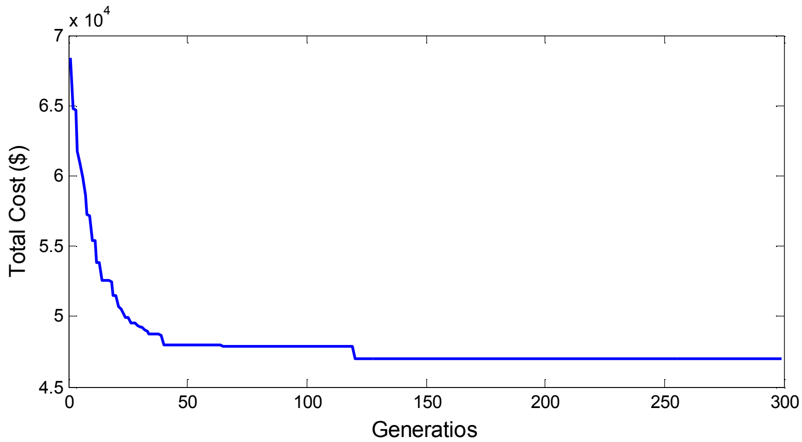


Figure VII.19 : *Typical performance of the GAGE in case Algerian network system.*

Table VI.17 : Best individual-Generation schedule and costs obtained by GAGE for Algerian network system.

Hour	Production Cost ($)	Transition Cost ($)	Spinning Reserve [MW]	Generation schedule (MW)									
				Unit 1	Unit 2	Unit 3	Unit 4	Unit 5	Unit 6	Unit 7	Unit 8	Unit 9	Unit 10
1	3367.53	0	1790	0	0	365.50	365.5	0	0	0	0	0	0
2	2839.00	26	2720	72	0	319.00	319.0	0	0	0	0	0	0
3	1667.16	397	1014	72	15.00	88.82	88.82	15.00	15.00	100	100	168.34	0
4	1664.15	0	1015	72	14.91	88.65	88.65	15.00	14.91	100	100	167.85	0
5	1655.15	0	1018	72	14.65	88.14	88.14	15.00	14.65	100	100	166.40	0
6	1543.17	500	1488	72	10.00	73.69	73.69	15.00	10.00	100	100	125.46	73.69
7	1556.96	0	1483	72	10.00	74.26	74.26	15.00	10.00	100	100	127.09	74.26
8	1683.27	0	1438	72	10.40	79.63	79.63	15.00	10.40	100	100	142.29	79.63
9	1832.04	0	1387	72	14.13	87.09	87.09	15.00	14.13	100	100	163.43	87.09
10	1901.25	0	1364	72	15.76	90.35	90.35	15.76	15.76	100	100	172.65	90.35
11	1944.02	0	1350	72	17.05	92.94	92.94	17.05	17.05	100	100	175.00	92.94
12	1950.19	0	1348	72	17.28	93.38	93.38	17.28	17.28	100	100	175.00	93.38
13	1965.67	0	1343	72	17.83	94.49	94.49	17.83	17.83	100	100	175.00	94.49
14	2041.32	0	1319	72	20.50	99.83	99.83	20.50	20.50	100	100	175.00	99.83
15	2031.74	0	1322	72	20.16	99.16	99.16	20.16	20.16	100	100	175.00	99.16
16	1987.51	0	1336	72	18.61	96.05	96.05	18.61	18.61	100	100	175.00	96.05
17	1886.09	0	1369	72	15.42	89.66	89.66	15.42	15.42	100	100	170.72	89.66
18	1805.32	0	1396	72	13.47	85.77	85.77	15.00	13.47	100	100	159.70	85.77
19	1758.31	0	1412	72	12.30	83.43	83.43	15.00	12.30	100	100	153.07	83.43
20	1864.98	0	1376	72	14.94	88.70	88.70	15.00	14.94	100	100	168.00	88.70
21	2109.29	0	1298	72	22.83	104.49	104.49	22.83	22.83	100	100	175.00	104.49
22	2145.56	0	1287	72	24.05	106.94	106.94	24.05	24.05	100	100	175.00	106.94
23	1993.79	0	1334	72	18.83	96.49	96.49	18.83	18.83	100	100	175.00	96.49
24	1864.98	0	1376	72	14.94	88.70	88.70	15.00	14.94	100	100	168.00	88.70
Total	**47,058.5631**	**923**	**29524**	Total generation cost ($):				**47,981.5631**					

Table VI.19 : Comparison with other variant GA.

Methods	Best ($)	Average ($)	Worst ($)
GA	48,904.64	49,392.22	49,751.77
RCGA	48,781.25	48,580.32	49,291.92
GAGE	47,981.56	48,102.10	48,533.22

Tables VI.9 show the results of the proposed method comparing with other variant GA method results, the obtained result in this section represents a nearer global optimal solution to the problem and verifies the correctness of the proposed algorithm.

VII.4. Conclusion :

In this chapter we try to simulate how the roots look for water under the ground, we try to found an algorithm; (RTO) which finds the optimal values to solve such problem.

We developed by using three kinds of gathered roots which create a new generation according to the previous one, the first one is to create a group of roots near from the wetter roots –the best- of the previous generation in order to exist more in that place, the second one is the roots which take the same previous direction, these ones are created from those roots which have a considerable witness degree with a random addition that locked with the augmentation of the generation number, the last one is the random roots instead of the weak ones in order to add and to avoid the local solution.

In the first section we clarify the efficiency of this method by its experiment on some known functions and by comparing it to recent techniques, where we find that it can find a new way of solution, one of its characteristics is the largest field of research due to the behavior of the roots.

Secondly, A new algorithm GAGE has been proposed to solve discrete optimisation problems, which is inspired by the Genetic Engineering operation on the GA. In GAGE, the modified GA includes cycles where new elite genes are evolved, and a new population that is richer in superior genes is generated. GAGE is efficiently applied to solve the UCP. The propose method is a combination of GAGE and the conventional Lambda-iteration method, which includes some other constraints. The total production costs of GAGE over the scheduled period are less expensive than the conventional genetic algorithm and the algorithms proposed the recent literature.

General conclusions

✓ Introduction

One of the main objectives when controlling power generation systems, to make the best use of available resources of generation to satisfy the instantaneous variations in the load demand without violating any of the constraints existing in the system. The various constraints arise in a power system from the operational limitations of the generating units and their accessories. Active power generated in a power system is controlled in tow time based loops: Economic Dispatch and Unit Commitment. Unit Commitment and Economic Dispatch loops schedule the generating resources to meet the forecasted load demand by continuously monitoring the load variations and adjusting the generation accordingly. This also ensures efficient constant frequency operation [237].

Review of various existing methods for the scheduling problems in power system is carried out. All these methods are proved to be efficient. The main objective of the work is to solve the scheduling problems in the power generation using a new and efficient method and to propose a simple and improved new algorithm to solve different types of ED problem viz, ED with prohibited zones and ramp-rate limit constraints, security constrained ED**.**

✓ Summary and Major Findings

The review on the existing solution strategies led to the scope of developing efficient scheduling methods in the field of power generation. our proposed methods are a good solution strategies and has been used for solution in many optimization tasks. In this thesis, efficient solutions are proposed for solution of the dispatch and scheduling problems in the power generation sector.

- **Economic Dispatch Problem**

As the first stage of the work, Economic load dispatch problem has been solved using various algorithms have been proposed such as GA, PSO, PS, BB-BC and ABC. The proposed algorithms have been successfully validated with classical and intelligent techniques of economic load dispatch and hence has reduced total fuel cost and power loss. The different proposed algorithms are applied in a ED, ED with valve-point effects and Combined Economic Emission Dispatch (CEED) environment. The advantages of the algorithms is demonstrated through simulations on different IEEE test systems.

In order to develop a solution strategy to handle larger problems, propose a new hybrid algorithm (GA–PS, PSO–PS, HBB–BC) for solving the EDP, the proposed methods are tested and validated on various electrical test systems and cases taking into different constraints, the results show that the optimal dispatch solutions determined, which confirms that the different algorithms are well capable of determining the global or near global optimum dispatch solution, the simulation results clearly show that the proposed hybrid methods can be used as an optimizer providing satisfactory solutions compared to the first methods.

In this thesis we introduce a new method for optimization that is called root tree optimization algorithm (RTO), which was developed and extracted from the movement of the plants root when they look for the nearest place of water, in this algorithm we lean on the behavior of the desert plants especially where the water resources lacked. The robustness and efficiency of the proposed new method is validated on nonlinear functions (different IEEE test systems) and compared to recent methods addressing the same problem, our simulation results illustrate that the performance of the proposed algorithm can efficiently handle stochastic cost functions, also RTO algorithms are found to take lesser computation time compared to other stochastic solution methods.

- **Unit Commitment Problem**

One of the disadvantages of traditional genetic algorithms is premature convergence because the selection operator depends on the quality of the individual, with the result that the genetic information of the best individuals tends to dominate the characteristics of the population [181]. Furthermore, when the representation of the chromosome is linear, the crossover is sensitive to the encoding or depends on the gene position. The ends of this type of chromosome have only a very low probability of changing by mutation. In this work a genetic algorithm is applied to the unit commitment problem using an annular crossover operator where the chromosome is in the shape of a ring, and a modified operator. The results obtained show that, with the application of the proposed operators to the unit commitment problem, better convergences and solutions are obtained than with the application of traditional genetic operators.

first of all, an RCGA is developed to solve the UC problem. In the proposed GA, the initial populations generated are such that it totally avoids the penalty functions. The populations evolved in the consecutive generations are repaired and approximated regarding the constraint violation of minimum up/down time constraints and demand/spinning reserve constraints. The effectiveness of the proposed algorithm has been tested on a number of sample systems. The investigations reveal that the proposed RCGA is simple, reliable and efficient.

Secondly, A new algorithm GAGE has been proposed to solve discrete optimisation problems, which is inspired by the Genetic Engineering operation on the GA. In GAGE, the modified GA includes cycles where new elite genes are evolved, and a new population that is richer in superior genes is generated. GAGE is efficiently applied to solve the UCP. The propose method is a combination of GAGE and the conventional Lambda-iteration method, which includes some other constraints. The total production costs of GAGE over the scheduled period are less expensive than the conventional genetic algorithm and the algorithms proposed the recent literature.

✓ **Scope for future research**

The proposed GAGE to solve the unit commitment problem with security constraints could be extended with bus voltage limits, limits on reactive power generation, tap-changing and phase-shifting transformers. The unit commitment problem could also be extended with load shedding and scheduled outages.

The unit commitment problem can be solved using hybrid artificial intelligent techniques to improve the computational speed. Hence the present approach and the results presented in this work will encourage further research in this field.

The RTO and GAGE algorithms developed in this thesis will be extremely useful for electric power utilities for enhancing the various types *of* economic dispatch problems and the unit commitment scheduling problem in an electric power system.

Appendix

Appendix. 1 :

Table A.1: Generator cost coefficients for 30 IEEE bus system.

Bus N°	**Real power output limit (MW)**		**Cost coefficients**		
	Min	**Max**	***a***	***b***	***c***
1	50	200	0.00375	2.00	0
2	20	80	0.01750	1.75	0
5	15	50	0.06250	1.00	0
8	10	35	0.00834	3.25	0
11	10	30	0.02500	3.00	0
13	12	40	0.02500	3.00	0

Table A.2: Generator cost coefficients for 30 IEEE bus system

Bus N°	**Real power output limit (MW)**		**Cost coefficients**				
	Min	**Max**	***a***	***b***	***c***	***e***	***f***
1	50	200	0.00160	2.00	150	50	0.063
2	20	80	0.01000	2.50	25	40	0.098

Appendix. 2 :

Table A.3: Generating unit data of 15 units system.

Unit	Output limit (MW)		Cost Coefficients		
	Min	Max	a	b	c
1	150	455	671	10.1	0.000299
2	150	455	574	10.2	0.000183
3	20	130	374	8.8	0.001126
4	20	130	374	8.8	0.001126
5	150	470	461	10.4	0.000205
6	135	460	630	10.1	0.000301
7	135	465	548	9.8	0.000364
8	60	300	227	11.2	0.000338
9	25	162	173	11.2	0.000807
10	25	160	175	10.7	0.001203
11	20	80	186	10.2	0.003586
12	20	80	230	9.9	0.005513
13	25	85	225	13.1	0.000371
14	15	55	309	12.1	0.001929
15	15	55	323	12.4	0.004447

The loss coefficients β matrices of 15 generating units :

$$B = \begin{bmatrix}
0.0014 & 0.0012 & 0.0007 & -0.0001 & -0.0003 & -0.0001 & -0.0001 & -0.0001 & -0.0003 & 0.0005 & -0.0003 & -0.0002 & 0.0004 & 0.0003 & -0.0001 \\
0.0012 & 0.0015 & 0.0013 & 0.0000 & -0.0005 & -0.0002 & 0.0000 & 0.0001 & -0.0002 & -0.0004 & -0.0004 & -0.0000 & 0.0004 & 0.0010 & -0.0002 \\
0.0007 & 0.0013 & 0.0076 & -0.0001 & -0.0013 & -0.0009 & -0.0001 & 0.0000 & -0.0008 & -0.0012 & -0.0017 & -0.0000 & -0.0026 & 0.0111 & -0.0028 \\
-0.0001 & 0.0000 & -0.0001 & 0.0034 & -0.0007 & -0.0004 & 0.0011 & 0.0050 & 0.0029 & 0.0032 & -0.0011 & -0.0000 & 0.0001 & 0.0001 & -0.0026 \\
-0.0003 & -0.0005 & -0.0013 & -0.0007 & 0.0090 & 0.0014 & -0.0003 & -0.0012 & -0.0010 & -0.0013 & 0.0007 & -0.0002 & -0.0002 & -0.0024 & -0.0003 \\
-0.0001 & -0.0002 & -0.0009 & -0.0004 & 0.0014 & 0.0016 & -0.0000 & -0.0006 & -0.0005 & -0.0008 & 0.0011 & -0.0001 & -0.0002 & -0.0017 & 0.0003 \\
-0.0001 & 0.0000 & -0.0001 & 0.0011 & -0.0003 & -0.0000 & 0.0015 & 0.0017 & 0.0015 & 0.0009 & -0.0005 & 0.0007 & -0.0000 & -0.0002 & -0.0008 \\
-0.0001 & 0.0001 & 0.0000 & 0.0050 & -0.0012 & -0.0006 & 0.0017 & 0.0168 & 0.0082 & 0.0079 & -0.0023 & -0.0036 & 0.0001 & 0.0005 & -0.0078 \\
-0.0003 & -0.0002 & -0.0008 & 0.0029 & -0.0010 & -0.0005 & 0.0015 & 0.0082 & 0.0129 & 0.0116 & -0.0021 & -0.0025 & 0.0007 & -0.0012 & -0.0072 \\
-0.0005 & -0.0004 & -0.0012 & 0.0032 & -0.0013 & -0.0008 & 0.0009 & 0.0079 & 0.0116 & 0.0200 & -0.0027 & -0.0034 & 0.0009 & -0.0011 & -0.0088 \\
-0.0003 & -0.0004 & -0.0017 & -0.0011 & 0.0007 & 0.0011 & -0.0005 & -0.0023 & -0.0021 & -0.0027 & 0.0140 & 0.0001 & 0.0004 & -0.0038 & 0.0168 \\
-0.0002 & -0.0000 & -0.0000 & -0.0000 & -0.0002 & -0.0001 & 0.0007 & -0.0036 & -0.0025 & -0.0034 & 0.0001 & 0.0054 & -0.0001 & -0.0004 & 0.0028 \\
0.0004 & 0.0004 & -0.0026 & 0.0001 & -0.0002 & -0.0002 & -0.0000 & 0.0001 & 0.0007 & 0.0009 & 0.0004 & -0.0001 & 0.0103 & -0.0101 & 0.0028 \\
0.0003 & 0.0010 & 0.0111 & 0.0001 & -0.0024 & -0.0017 & -0.0002 & 0.0005 & -0.0012 & -0.0011 & -0.0038 & -0.0004 & -0.0101 & 0.0578 & -0.0094 \\
-0.0001 & -0.0002 & -0.0028 & -0.0026 & -0.0003 & 0.0003 & -0.0008 & -0.0078 & -0.0072 & -0.0088 & 0.0168 & 0.0028 & 0.0028 & -0.0094 & 0.1283
\end{bmatrix}$$

B_{oi}=[-0.0001 -0.0002 0.0028 -0.0001 0.0001 -0.0003 -0.0002 -0.0002 0.0006 0.0039 -0.0017 -0.0000 -0.0032 0.0067 -0.0064]

B_{oo}= 0.055.

Appendix. 3 :

Table A.4 : Fuel Cost coefficients.

Generator N°	a_i	b_i	c_i	P_{max} [p.u]	P_{min} [p.u]
1	100	200	10	0.50	0.02
2	120	150	10	0.60	0.03
3	40	180	20	1.00	0.05

Table A.5 : NO_x Emission coefficients.

Generator N°	gi_{NOx}	hi_{NOx}	ki_{NOx}
1	0.5783298	0.00816466	1.6103e-6
2	0.3515338	0.00891174	2.1999e-6
3	0.0884504	0.00903782	5.4658e-6

Table A.6 : SO2 Emission coefficients.

Generator N°	di_{SO2}	ei_{SO2}	fi_{SO2}
1	0.04373254	-9.4868099e-5	1.4721848e-7
2	0.055821713	-9.7252878e-5	3.0207577e-7
3	0.027731524	-3.5373734e-4	1.9338531e-6

Appendix. 4 :

Table A.7 : Generator data of three unit test system.

Units	P^i_{min}	P^i_{max}	*a*	*b*	*c*	*e*	*f*
1	100	600	0.001562	7.92	561	300	0.0315
2	50	200	0.004820	7.97	78	150	0.063
3	100	400	0.001940	7.85	310	200	0.042

Table A.8 : Generator data of 15 unit test system.

Units	$P^i_{\min}$	$P^i_{\max}$	*a*	*b*	*c*	*e*	*f*
1	0	680	0.00028	8.10	550	300	0.035
2	0	360	0.00056	8.10	309	200	0.042
3	0	360	0.00056	8.10	307	150	0.042
4	60	180	0.00324	7.74	240	150	0.063
5	60	180	0.00324	7.74	240	150	0.063
6	60	180	0.00324	7.74	240	150	0.063
7	60	180	0.00324	7.74	240	150	0.063
8	60	180	0.00324	7.74	240	150	0.063
9	60	180	0.00324	7.74	240	150	0.063
10	40	120	0.00284	8.60	126	100	0.084
11	40	120	0.00284	8.60	126	100	0.084
12	55	120	0.00284	8.60	126	100	0.084
13	55	120	0.00284	8.60	126	100	0.084

Appendix. 5 :

Generalized loss coefficient for IEEE-30 bus test system:

$$B = \begin{bmatrix} 0.1382 & -0.0299 & 0.0044 & -0.0022 & -0.0010 & -0.0008 \\ -0.0299 & 0.0487 & -0.0025 & 0.0004 & 0.0016 & 0.0041 \\ 0.0044 & -0.0025 & 0.0182 & -0.0070 & -0.0066 & -0.0066 \\ -0.0022 & 0.0004 & -0.0070 & 0.0137 & 0.0050 & 0.0033 \\ -0.0010 & 0.0016 & -0.0066 & 0.0050 & 0.0109 & 0.0005 \\ -0.0008 & 0.0041 & -0.0066 & 0.0033 & 0.0005 & 0.0244 \end{bmatrix}$$

$$Boi = [\ -0.0107 \quad 0.0060 \quad -0.0017 \quad 0.0009 \quad 0.0002 \quad 0.0030\ ];$$

$$Boo = 9.8573e-4;$$

Table A.9 : Cost coefficients IEEE 30-bus test system.

Generator N°	a_i	b_i	c_i	P_{max} (p.u)	P_{min} (p.u)
1	100	200	10	0.50	0.02
2	120	150	10	0.60	0.03
3	40	180	20	1.00	0.05
4	60	100	10	1.20	0.06
5	40	180	20	1.00	0.05
6	100	150	10	0.60	0.03

Table A.10 : Cost emission IEEE 30-bus test system.

Generator N°	α_i	β_i	γ_i	ζ_i	λ_i
1	*4.091*	*-5.554*	*6.490*	*2.0e-4*	*2.857*
2	*2.543*	*-6.047*	*5.638*	*5.0e-4*	*3.333*
3	*4.258*	*-5.094*	*4.586*	*1.0e-6*	*8.000*
4	*5.326*	*-3.550*	*3.380*	*2.0e-3*	*2.000*
5	*6.131*	*-5.555*	*5.151*	*1.0e-6*	*6.667*
6	*4.258*	*-5.094*	*4.586*	*1.0e-5*	*8,000*

Appendix. 6.

Table A .11 : Unit data of the 10-unit 24 hour test system.

	Unit 1	Unit 2	Unit 3	Unit 4	Unit 5	Unit 6	Unit 7	Unit 8	Unit 9	Unit 10
P^{max} (MW)	455	455	130	130	162	80	85	55	55	55
P^{min} (MW)	150	150	20	20	25	20	25	10	10	10
a_0	1000	970	700	680	450	370	480	660	665	670
a_1	16.19	17.26	16.60	16.50	19.70	22.26	27.74	25.92	27.27	27.79
a_2	0.00048	0.00031	0.002	0.00211	0.00398	0.00712	0.00079	0.00413	0.00222	0.00173
t_{up} (h)	8	8	5	5	6	3	3	1	1	1
t_{down} (h)	8	8	5	5	6	3	3	1	1	1
S_h($) (hot start)	4500	5000	550	560	900	170	260	30	30	30
S_c($) (cold start)	9000	10000	1100	1120	1800	340	520	60	60	60
$t_{cold\ start}$ (h)	5	5	4	4	4	2	2	0	0	0
Initial State (h)	8	8	-5	-5	-6	-3	-3	-1	-1	-1

Table A .12 : Demand of 10 unit 24 hour test system.

Hour	Load (MW)	Hour	Load (MW)	Hour	Load (MW)
1	700	9	1300	17	1000
2	750	10	1400	18	1100
3	850	11	1450	19	1200
4	950	12	1500	20	1400
5	1000	13	1400	21	1300
6	1100	14	1300	22	1100
7	1150	15	1200	23	900
8	1200	16	1050	24	800

Appendix. 7.

Table A .13 : Load and Reserve (Wood and Wollenberg 1996).

Hour	1	2	3	4	5	6	7	8
Demand (MW)	450	530	600	540	400	280	290	500
Reserve (MW)	45	53	60	54	40	28	29	50

Table A .14 : Test System (Wood and Wollenberg 1996).

	Unit 1	Unit 2	Unit 3	Unit 4
P^{max} (MW)	300	250	80	60
P^{min} (MW)	75	60	25	20
a_0	684.74	585.62	213.00	252.00
a_1	16.83	16.95	20.74	23.60
a_2	0.0021	0.0042	0.0018	0.0034
t_{up} (h)	5	5	4	1
t_{down} (h)	4	3	2	1
S_h($) (hot start)	500	170	150	0.00
S_c($) (cold start)	1100	400	350	0.02
$t_{cold\ start}$ (h)	5	5	4	0
Initial State (h)	8	8	-5	-6

Appendix. 8.

Table A .15 : Unit data of the Algerian network system.

	Unit 1	Unit 2	Unit 3	Unit 4	Unit 5	Unit 6	Unit 7	Unit 8	Unit 9	Unit 10
P^{max} (MW)	72	70	510	400	150	100	100	140	175	450
P^{min} (MW)	8	10	30	20	15	10	10	15	18	30
a_0	0	0	0	0	0	0	0	0	0	0
a_1	1.5	2.5	1.5	1.5	2.5	2.5	2	2	2	1.5
a_2	0.0085	0.0170	0.0085	0.0085	0.0170	0.0170	0.0030	0.0030	0.0030	0.0085
t_{up} (h)	1	2	5	5	2	2	2	2	2	5
t_{down} (h)	1	2	5	5	2	2	2	2	2	1
S_h($) (hot start)	26	17	500	500	90	55	55	90	90	500
S_c($) (cold start)	26	17	500	500	90	55	55	90	90	500
$t_{cold\ start}$ (h)	2	2	4	4	2	2	2	2	2	4
Initial State (h)	0	0	0	0	0	0	0	0	0	0

Table A .16 : Demand of Algerian network system.

Hour	Load (MW)	Hour	Load (MW)	Hour	Load (MW)
1	731	9	780	17	798
2	710	10	803	18	771
3	703	11	817	19	755
4	702	12	819	20	791
5	699	13	824	21	869
6	679	14	848	22	880
7	684	15	845	23	833
8	729	16	831	24	791

References

[1] M. Sudhakaran, P. Ajay-D-Vimal Raj, Integrating genetic algorithms and tabu search for unit commitment problem, nternational Journal of Engineering, Science and Technology, 2(1):57-69, 2010.

[2] F.Shaikh, P.H. Shaikh, M. Mirani, M.A. Uqaili, Multi Criteria Optimization Algorithm for Economic Dispatch Complications for Sustainable Interconnected Power System, International Journal of Computer Applications, 50(4):22-25, 2012.

[3] Kankar Bhattacharya, Math H. J. Bollen, Jaap E. Daalder, Operation of Restructured Power Systems, The Kluwer International Series in Engineering and Computer Science, 2001.

[4] P. Ajay-D-Vimal Raj, Performance Evaluation Of Swarm Intelligence Based Power System Optimization Strategies. PhD thesis, Pondlcherry University, 2008.

[5] D. P. Kothari and J. S. Dhilon, Power System Optimization. New Delhi: Prentice-Hall of India. 2004.

[6] L. Lei Lai., Intelligent System Applications In Power Engineering, New York: John Wiley & Sons Ltd., 1996.

[7] J. Kennedy, R. Eberhart., Particle Swarm Optimization. Proceedings of IEEE International Conference on Neural Networks. 4:1942-1948, 1995.

[8] B. Sttot, J. L. Marinho, Linear programming for power system network security applications, IEEE Trans. On Power Systems, PAS-98(3): 837-848, May/June 1979.

[9] O. Alsac, J. Bright, M. Prais, and B. Scott Further developments In LP based optimal power flow," IEEE Trans. Power Systems, 5(3):697-711, 1990.

[10] G.T. Heydt and W.M. Grady, Optimal VAR siting using linear load flow fonnulatiorr, IEEE Trans. Power Apparatus and Systems, 5(PAS-102):1214-1222, 1983.

[11] G.D. Irrisari, L.M. Kimball, K.A. Clements, A. Bagchi, and P. W. Davis, Economic dispatch with network and ramping constraints via interior point methods, IEEE Trans. Power Systems, 13:236-242, 1998

[12] L.S. Vargas. V.H. Quintana, and V. Vannelli, A tutorial description of an Interior point method and its applications to security constrained economic dispatch, IEEE Trans. Power Systems, 8(3):1315-1324, 1993.

[13] S. Granville, Optimal reactive dispatch through interior pant methods. IEFE Trans. Power $stems. 9(1):136-144, 1994.

[14] J. Riquelme Santos. Alicia Troncoso Lora. Antonlo Gomet Exposito and Jose Luiz Martinez Ramos, Finding improved local minima of power system optimization problems by interior-point methods, IEEE Trans Power Systems, 18(1):238-244, Feb. 2003.

[15] M. Christoforidis, M. Aganagic. B. Awobamise. S. Tong. and A.F. Rahimi, Long-term/Mid-term resource optimization of a hydro-dominant power system using interior point methods, IEEE Trans Power Systems, II(I):287-294, 1986.

[16] J.C.O. Mello, A.C.G. Melo, and S. Ciranville, Simultaneous capability assessment by combining interior point method and Monte Carlo simulation. IEEE Trans Power Systems, 12(2):736.747, 1997.

[17] K. Ponnambalam, V.H. Quintana. and A. Vannelli, A fast algorithm for power system optimization using interior point method. IEEE Trans. Power Systems, 7(2):892-899, 1992.

[18] V.R. Sherkat and Y. Ikura, Experience with interior point optimization software for a fuel planning application. IEEE Trans. Power Systems. 9(2):833-840, 1994.

[19] J.A. Momoh, S.X. Guo, E.C. Ogbuoriri, and R. Adapa, The quadratic interior point method solving power system optimization problems, IEEE Trans. Power Systems, 9(3):1327-1336, 1994.

[20] J. Nanda, D.P. Kothari, and S.C. Srivastava, A new optimal power dispatch algorithm using fletcher's QP method. IEE Proc.- Generation. Transmission and Distribution, 136(3): 153-161, 1989.

[21] G. Opoku, Optimal power system VAR planning. IEEE Trans. Power System, 5(1):53-59, 1990.

[22] M. Chebbo and M.R. Irving, Combined active and reactive power dispatch Part 1. problem formulation and solution algorithm. IEE Pro-Generation. Transmission and Distribution, 142(4):393-400, 1995.

[23] M. Chebbo, M.R. Irving. and N.H. Dandachi, Combined active and reactive power dispatch Part 2: test results. IEE Pro-Generation. Transmission and Distribution, 142(4):401-405, 1995

[24] M. R. Irving and Y. H. Song, Optimization methods or electric power systems, Part 1, Mathematical Optimization Methods. IEE Power Engineering Journal, 14(5):245-254, 2000.

[25] W.F. Tlnney and C.S. Hart, Power flow solution by newton's method. IEEE Trans. Power Apparatus and Systems, 85(1):1440-1400, 1967.

[26] D.I. Sun, B. Ashley, B. Brewer, A. Hughes. and W. I. Tinney, Optimal power flow by newton approach. IEEE Tran. Power Apparatus and .Systems, 103(2):2864-2878, 1984.

[27] Xiaohong Guan Luh and P.B. Lan Zhang, Nonlinear approximation method in lagrangian relaxation-based algorithms for hydrothermal scheduling. IEEE Trans. Power Systems, 10(2):772-778, 1995.

[28] K. Aoki, M. Fan, and A. Nishikori, Optimal VAR planning by approximation method for recursive mixed - integer linear programming. IEEE Trans Power Systems, 3(4):1741-1747, 1988.

[29] R. Adams and M. A. Laughton, Optimal planning of power networks using mixed integer programming. IEE Proc.-Generation. Transmission and Distribution, 121(2):139-145, 1974.

[30] T. Gonen and B.L. Foote, Distribution system planning using mixed integer programming. IEE Proc.-Generation.Transmission and Distribution, 128(2):70-79, 1981.

[31] T. S. Dillon, K.W. Edwin, H. D. Kochs, and R. D. Tand, Integer programming approach to the problem of unit commitment with probabilistic reserve determination. IEEE Tram. Power Apparatus and Systems, 97(6):2154-2166, 1978.

[32] J.F. Dapezo and H.M. Merill, Optimal generator scheduling with Integer programming. IEEE Trans Power Apparatus and Systems, 93(7):1537-1545, 1975

[33] Y.H. Song, Modern optimization techniques in power systems. London, CIK Kluwer Academic, 1999

[34] F.C. Lu and Y.Y Hsu, Reactive power voltage control In a distribution substation using dynamic programming. IEE Proc-Generation Transmission and Distribution. 142(6):639-645, 1995.

[35] J. Parten, A simplified modified dynamic programming algorithm for s171ng location and feeder reinforcements. IEEE Trans. Power Delivery, 5(I):277-283, 1990.

[36] W.J. liobbs, G Hernlon, S. Warner, and C. B Shehle, An enhanced dynamic approach for unit commitment. IEEE Trans Power Systems, 3(3):1201-1205, 1988.

[37] K.Y. Lee and M.A. El-Sharkawl, Modem heuristic optimization techniques with applications to power systems, IEEE Power Engineering Society (02TP160), 2002.

[38] P. N. Suganthan, Particle swam optimizer with neighborhood operator. In Proc. Evolutionary Computation Congress, 3:1958-1962, 1999.

[39] Carlos A. Coello, Gregorio Toscano Pulido and Maximino Saluar Lechuga, Handling multiple objectives with particle swarm optimization. IEEE Trans. Evolutionary Computation, 8(3):256-279, June 2004.

[40] P. Angeline, Using selection to improve particle swam optimizat1on. In Proceedings of the 1998 IEEE International Conference on Evolutionary Computation, Anchorage, AK,84–89, 1998.

[41] Y. Shi and R. Eberhart, Parameter selection in particle swarm optimization. Proc. Seventh Annual Conf. on Evolutionary Programming, 591-601, 1998.

[42] I. Wood and B.F. Wollenberg, Power Generation Operation und Control. New York: John Wiley & Sons, 1996.

[43] Zwe-Lee Gaing, Particle swarm optimization to solving the economic dispatch considering the generator constraints. IEEE Trans. Power Systems, 18(3):1187-1195, Aug. 2003.

[44] D.N. Jeyakumar, T. layabarathi, and T. Raghunathan, Particle swarm optimization for various types of economic dispatch problems. International Journal of Electrical Power und Energy Systems, 28(1):36-42. Jan 2006.

[45] J.W. Talaq, M.E. El-Haway, and F-El Hanvay, A summary of environmental/economic dispatch algorithms, IEEE Trans. Power Systems, 3:1508-1516, 1994.

[46] K.P. Wong, J. Yurevich, Evolutionary programming based algorithm for environmentally-constrained economic dispatch. IEEE Trans Power Systems. 13(2):301-306, May 1998.

[47] P. Venkatesh, R. Gnanadass, and Nardyana Prasad Pady, Comparison and application of evolutionary programming techniques to combined economic emission dispatch with Fine flow constraints. IEEE Trans Power System, 18(2): 688-697, Feb. 2003.

[48] M.A. Abido, Multi-objective evolutionary algorithms for eclectic power dispatch problem. IEEE Trans. Evolutionary Computation, 10(3): 315-329, June 2006.

[49] D.C. Walters, G.B. Sheble, Genetic algorithm solution of economic dispatch with valve point loading. IEEE Trans. Power Systems, 8(3):1325-1332, Aug. 1993.

[50] K.P. Wong, Y.W. Won, Genetic and genetic/simulated-annealing approaches to economic dispatch. IEE Proc.-Generation. Transmission and Distribution, pt. C, 141(5):507-513, Sep. 1994.

[51] P.H. Chen and H.C. Chang, Large scale economic dispatch by genetic algorithm. IEEE Trans Power Systems, 10(4):1919-1926. Nov. 1995.

[52] C. Fung. S.Y. Chow, and K.P. Wong, Solving the economic dispatch problem with an integrated parallel genetic algorithm. In Proc. IEEE Power System technology Conf., 3:1257-1262, 2001.

[53] El-Gallad, M. El-Hawary, A.A. Sallam. and A. Kalas, Swarm intelligence for hybrid cost dispatch problem. In Proc. Canadian Electrical Computer Engineering Conf., 2:753-757, 2001.

[54] El-Gallad, M. El-Hawary, A.A. Sallam, and A. Kalas, Particle swarm optimizer for constrained economic dispatch with prohibited operating zones. In Proc. Canadian Elect. Computer Engineering Conf, I:78-81, 2002.

[55] L.L. Lai, T.Y. Nieh, D. Vujatovic. Y.N. Ma, Y.P. Lu, Y.W. Yang, and H. Braun, Particle swarm optimization for economic dispatch of units with non- smooth input-output characteristic functions. In Proc. Intelligent System Applications to Power Systems. 499-503, 2005.

[56] T.A.A. Victoire and A.E. Jcyakumar, Reserve constrained dynamic dispatch of units with valve-point effects. IEEE Trans Power Systems, 20(3):1273-1282. Aug. 2005.

[57] Tim T. Maifeld and Gerald B. Sheble, Genetic-based unit commitment algorithm. IEEE Trans. Power Systems, 11(3):1359-1370, Aug. 1996.

[58] S.A. Kazarlis, A.G. Bakirtzis, and V. Petridis, A Generic algorithm solution to the unit commitment problem. IEEE Trans. Power Systems, II(I):83-92, Feb. 1996.

[59] K.S. Swarp and S. Yamashiro, Unit commitment solution methodology using genetic algorithm. IEEE Trans. Power Systems, 17:87-91, Feb. 2002.

[60] Zwe-Lee Gaing, Discrete particle swarm optimization algorithm for unit commitment. In Proc. IEEE Power Engineering Society General Meeting, 1:418-424, 2003.

[61] Zhao C.X. Guo, B.R. Bai, and Y.J. Cao, An improved particle swarm optimization algorithm for urn1 commitment. International Journal of Electrical Power and Engineering, 28(I):482-490, Jan. 2006.

[62] T.O. Ting, M.V.C. Rao, C.K. Loo, A novel approach for unit commitment problem via an effective hybrid particle swarm optimization. IEEE Trans. Power Systems, 21(I):411-418, Fcb. 2006.

[63] A. Y. Saber, T. Senjyu, A. Yona, N. lirasaki, T. Funabashi, Fuzzy unit commitment solution-A novel twofold simulated annealing approach. Electric Power Systems Research, 77:1699-1712, 2007.

[64] Saumendra Sarangi, Particle Swarm Optimisation applied to Economic Load Dispatch problem, PhD thesis, National Institute of Technology, Rourkela, 2009.

[65] H. Mori, K. Okawa, A new meta-heuristic method for profit-based unit commitment under competitive environment. IEEE Bucharest PowerTech 2009, 1-6.

[66] T.A.A. Vlcloire and A.E. Jeyakumar, Unit commitment by a tabu-search- based hybrid-optimization technique. IEE Proc. Generation. Transmission and Distribution, 152(4):503-574, Jul. 2005.

[67] H. Mantawy and M.S. Al-Ghamdi, A new reactrve power optimization algorithm. In Proc. IEEE Power Tech. Con. 2003, 4:6-11.

[68] A.A.A. Esmin, G. Lambert-Torres, A.C.Z. de Souza, A hybrid particle swarm optimization applied to loss power minimization. IEEE Trans. Power Systems, 20(2): 859-866, May 2005.

[69] M. Tripathy and S. Mishra, Bacteria foraging-based solution to optimize both real power loss and voltage stability limit. IEEE Trans. Power Systems, 22(1):240-248, Feb. 2007.

[70] Yair Malachi and Sigrnond Singer, A genetic algorithm for the corrective control of voltage and reactive power," IEEE Trans Power Systems, 21(I):295-300, Feb. 2006.

[71] Amgad A. EL-Dib. Hosam K.M. Youssef. M.M EL-Metwally, Z. Osman, Optimum VAR sizing and allocation using particle swarm optimization. Electric Power Systems Research, 77: 965-972, 2007.

[72] Yuan, X., L. Wang, Y. Zhang, Y. Yuan, A hybrid differential evolution method for dynamic economic dispatch with valve-point effects. Expert Systems with Applications, 36:4042–4048, 2009.

[73] Xia, X., A.M. Elaiw, Optimal dynamic economic dispatch of generation: A review. Electric Power System Research, 80:975–986. 2010.

[74] Han, X.S., H.B. Gooi, Effective economic dispatch model and algorithm. Electrical Power and Energy Systems, 29:113–120, 2007.

[75] P. Attaviriyanupap, H. Kita, E. Tanaka, and J. Hasegawa, A hybrid EP and SQP for dynamic economic dispatch with nonsmooth fuel cost function. IEEE TRANS. ON POWER SYSTEMS, 17:411–416, 2002.

[76] Li F., R. Morgan, D. Williams, Hybrid genetic approaches to ramping rate constrained dynamic economic dispatch. Electric Power System Research, 43:97–103, 1997.

[77] Ingrida Radziukyniene, C-GRASP application to the economic dispatch problem, PhD thesis, university of florida, 2010.

[78] Han, X.S., and D.S. Kirschen H.B. Gooi, Dynamic Economic Dispatch: Feasible and Optimal Solutions. IEEE TRANSACTIONS ON POWER SYSTEMS, 16:22–28, 2001.

[79] Panigrahi, B.K., S.R. Yadav, S. Agrawal, M.K. Tiwari, A clonal algorithm to solve economic load dispatch. Electric Power System Research, 77:1381–1389, 2007.

[80] Yare, Y., G.K. Venayagamoorthy, A.Y. Saber, Heuristic Algorithms for Solving Convex and Nonconvex Economic Dispatch. The 15th International Conference on Intelligent Sys. Applications to Pow. Systems, 2009.

[81] Somuah, C.B., N. Khunaizi, Application of linear programming redispatch technique to dynamic generation allocation. IEEE TRANSACTIONS ON POWER SYSTEMS, 5:20–26, 1990.

[82] Zarei, M., A. Roozegar, R. Kazemzadeh, J.M. Kauffmann, Two Area Power Systems Economic Dispatch Problem Solving Considering Transmission Capacity Constraints. World Academy of Science, Engineering and Technology, 33:147–152, 2007.

[83] Selvakumar, A.I., K. Thanushkodi, Optimization using civilized swarm: Solution to economic dispatch with multiple minima. Electric Power System Research, 79:8–16, 2009.

[84] Jabr, R.A., A.H. Coonick, B.J. Cory, A study of the homogeneous algorithm for dynamic economic dispatch with network constraints and transmission losses. IEEE Transactions On Power Systems, 15:605–611, 2000.

[85] Ongsakul, W., J. Tippayachai, Parallel micro genetic algorithm based on merit order loading solutions for constrained dynamic economic dispatch. Electric Power System Research, 61:77–88, 2002.

[86] C. Wang, S.M. Shahidehpour, Ramp-rate limits in unit commitment and economic dispatch incorporating rotor fatigue effect. IEEE Transactions On Power Systems, 9(3):1539–1545, 1994.

[87] T.A.A. Victoire, A.E. Jeyakumar, Hybrid PSOSQP for economic dispatch with valve-point effect. Electric Power System Research, 71:51–59, 2005.

[88] Selvakumar, A.I., K. Thanushkodi, Anti-predatory particle swarm optimization: Solution to nonconvex economic dispatch problems. Electric Power System Research, 78:2–10, 2008.

[89] Chiang, Ch.-L., Improved Genetic Algorithm for Power Economic Dispatch of Units With Valve-Point Effects and Multiple Fuels. IEEE Transactions On Power Systems, 20:1690–1699, 2005.

[90] Basu, M., Dynamic economic emission dispatch using nondominated sorting genetic algorithm-II. Electrical Power and Energy Systems, 30:140–149, 2008.

[91] Jizhong Zhu, Optimization of Power System Operation. John Wiley and Sons, New Jersey, 2009.

[92] Basu, M., Economic environmental dispatch of hydrothermal power system. Electrical Power and Energy Systems, 32:711–720, 2010.

[93] Brini, S., H.H. Abdallah, A. Ouali., Economic Dispatch for Power System included Wind and Solar Thermal energy. Leonardo Journal of Sciences, 14:204–220, 2009.

[94] Sun D.I, Ashley B, Brewer B, Hughes A and Tinney W.F, "Optimal Power Flow By Newton Approach," IEEE Transactions on Power Apparatus and Systems, vol.PAS-103, no.10, pp.2864-2880, Oct. 1984.

[95] Allen J. Wood and Bruce F. Wollenberg, Power Generation, Operation and Control. Wiley India, New Delhi, 2009.

[96] John J. Grainger and William D. Stevenson Jr., Power System Analysis. Tata McGraw-Hill, New Delhi, 2009.

[97] J. A. Momoh. Electric Power System Applications of Optimization. Power Engineering. Markel Dekker Inc.: New York, USA, 2001.

[98] Ravikanth Reddy Gaddam. Optimal Unit Commitment using Swarm Intelligence for Secure Operation of Solar Energy Integrated Smart Grid. Thesis, Power systems research center international institute of information technology Hyderabad, INDIA, April 2013

[99] Simopoulos, D and Kavatza, S, Consideration of ramp-rate constraints in unit commitment using simulated annealing: EEE Russia, Power Tech, 1-7, June 2005.

[100] Wang C, Shahidehpour S.M, Effects of ramp-rate limits on unit commitment and economic dispatch", IEEE Transactions on Power Systems, 8(3):1341-1350, Aug 1993.

[101] John A. Muckstadt and Richard C. Wilson, An application of mixed-integer programming duality to scheduling thermal generating systems. IEEE Transactions on Power Apparatus and Systems, PAS-87(12):1968-1978, Dec. 1968.

[102] Devendra Kumarn, shiwani Kumar, Lokesh Kumar Yadav, Unit Commitment of Thermal Power Plant in Integration With Wind and Solar Plant Using Genetic Algorithm, International Journal of Engineering Research & Technology (IJERT), 3(7):664-670, July 2014.

[103] Mitchell Melanie, An Introduction to Genetic Algorithms, A Bradford Book The MIT Press, Cambridge, Massachusetts • London, England, Fifth printing, 1999.

[104] C.J. Lakhmi, N.M. Martin, Fusion of Neural Networks, Fuzzy Systems and Genetic Algorithms: Industrial Applications (CRC Press), 1998.

[105] S. Rajasekaran & G.A. Vijayalakshmi Pai, Neural Networks, Fuzzy Logic and Genetic Algorithms: Synthesis & Applications, PHI, 2003.

[106] Eberhart, R.C. and Shi, Y., Particle swarm optimization: developments, applications and resources. Proc. congress on evolutionary computation 2001 IEEE service center, Piscataway, NJ., Seoul, Korea., 2001.

[107] Lewis R.M, Torczon V, Trosset M.W., Direct search methods: then and now. J of Computational and Applied Mathematics, 2000, 124: 191-207.

[108] Thitithamrongchai C, Eua-arporn B., Self-adaptive Differential Evolution Based Optimal Power Flow for Units with Non-smooth Fuel Cost Functions. J. Electrical Systems, 3(2): 88-99, 2007.

[109] Nur Gabere M. Simulated Annealing Driven Pattern Search Algorithms for Global Optimization. Master thesis, University of the Witwatersrand, Johannesburg, 2007

[110] Alberto P, Nogueira F, Rocha H, Vicente L N., Pattern search methods for user-provided points: Application to molecular geometry problems. SIAM Journal on Optimi, 14:1216-1236, 2004.

[111] K. Erol Osman, Ibrahim Eksin, New optimization method : Big Bang-Big Crunch", Elsevier, Advances in Engineering Software, 37:106–111, 2006.

[112] A. Kaveha, S. Talataharib, Size optimization of space trusses using Big Bang–Big Crunch algorithm", Elsevier, Computers and Structures, 87:1129–1140, 2009.

[113] Karaboga D., An idea based on honey bee swarm for numerical optimization. Technical Report-Tr06t, Computer Engineering Department, Engineering faculty, Erciyes University, Turkey, 2005

[114] Karaboga D, Basturk B., On the performance of artificial bee colony (ABC) algorithm. Applied Soft Computing, 8(1):687–697, 2008.

[115] Wang SK, Chiou JP, Liu CW., Non-smooth/non-convex economic dispatch by a novel hybrid differential evolution algorithm, IET Gener Transm Dis, 1:793-803, 2007.

[116] Gao H, Xu W., Particle swarm algorithm with hybrid mutation strategy, Appl Soft Comput, 11(8):5129-5142, 2011

[117] Jia DL, Zheng GX, Qu BY, Khan MK., A hybrid particle swarm optimization algorithm for high-dimensional problems, Comput Ind Eng, 61(4):1117-22, 2011.

[118] Erol Osman K., Eksin I., New optimization method: Big Bang-Big Crunch. Advances in Engineering Software, 37:106-111, 2006.

[119] Kaveh A, Talatahari S., A discrete Big Bang-Big Crunch algorithm for optimal design of skeletal structure, Asian J Civ Eng, 11(1):103–22, 2010.

[120] Serena H. Chen, Anthony J. Jakeman, John P. Norton, Artificial Intelligence techniques: An introductionto their use for modelling environmental systems. Mathematics and Computers in Simulation, 78: 379–400, Jan 2008.

[121] T. Baeck, D.B. Fogel and Z. Michalewicz, Handbook of Evolutionary Computation. Taylor & Francis, 1997.

[122] X.S. Yang, Nature-Inspired Metaheuristic Algorithms. Luniver Press, 2008.

[123] X.S. Yang, Engineering Optimization: An Introduction with Metaheuristic Applications. Wiley & Sons, New Jersey, 2010.

[124] X.S. Yang, Firefly algorithms for multimodal optimization. Stochastic Algorithms : Foundations and Appplications (Eds O. Watanabe and T. eugmann), SAGA 2009, LectureNotes in Computer Science, 5792, Springer-Verlag, Berlin, 169-178, 2009.

[125] S.N. Singh, S.C. Srivastava., A Genetic Algorithmand its Applications in Power System Problems. Proceedingsof tenth National Power System Conference NPSC, 1:289-296, 1998.

[126] R. Labdani, L. Slimani, T. Bouktir, Particle Swarm Optimization Applied to the Economic Dispatch Problem. J. Electrical Systems, 2(2):95-102, 2006.

[127] W. Ongsakul and T. Tantimaporn, Optimal powers flow by improved evolutionary programming. Elect. Power Comp. and Syst., 34:79-95, 2006.

[128] J. Yuryevich, K.P., Wong: Evolutionary Programming Based Optimal Power Flow Algorithm, IEEE Transaction on power Systems, 14(4):1245–1250, November 1999.

[129] C. Thitithamrongchai, B. Eua-arporn, Self-adaptive Differential Evolution Based Optimal Power Flow for Units with Non-smooth Fuel Cost Functions. J. Electrical Systems, 3(2):88-99, 2007.

[130] Saravuth Pothiya, Issarachai Ngamroo, Waree Kongprawechnon, Application of multiple tabu search algorithm to solve dynamic economic dispatch considering generator constraints. Elsevier, Energy Conversion and Management, 49:506–516, 2008.

[131] Gaing Zwe-Lee, Particle swarm optimization to solving the economic Dispatch considering the generator constraints. IEEE Trans Power Syst, 18(3):1187–95, 2003.

[132] T.F. Robert A. King and H.C.S. Rughooputh, Elitist Multiobjective Evolutionary Algorithm for Environmental/Economic Dispatch. Proceedings IEEE Congress on Evolutionary Computation (CEC2003), Australia, 2:1108-1114, 2003.

[133] C.A. Roa-Sepulveda, Environmental economic dispatch via hopfield neural network and Taboo search," UPEC'96 Universities Power Engineering Conference, Crete, Greece, 1996, 1001-1004.

[134] Victorie T.A.A, Jeyakumar A.E., Hybrid PSO-SQP for economic dispatch with valve-point effect. Electric Power Systems Research, 71(1):51–59, 2004.

[135] Sinha N, Chakrabarti R, Chattopadhyay P.K., Evolutionary programming techniques for economic load dispatch. IEEE Transactions on Evolutionary Computation, 7(1):83–94, 2003.

[136] Alsumait J.S, Al-Othman A.K, Sykulski J.K., Application of pattern search method to power system valve-point economic load dispatch. Electrical Power and Energy Systems, 29(10):720–730, 2007.

[137] Duman S, Güvenç U, Yörükeren N., Gravitational search algorithm for economic dispatch with valve-point effects. International Review of Electrical Engineering (I.R.E.E), 5(6):2890–2895, 2010.

[138] Dos Santos Coelho L, Mariani V.C., Particle swarm approach based on quantum mechanics and harmonic oscillator potential well for economic load dispatch with valve-point effects. Energy Conversion and Management, 49(11): 3080–3085, 2008.

[139] Chiang C.L., Improved genetic algorithm for economic dispatch of units with valve-point effects and multiple fuels. IEEE Transactions on Power Systems, 20(4): 1690–1699, 2005.

[140] He D-K, Wang F-L, Mao Z-Z., Hybrid genetic algorithm for economic dispatch with valve point effect. Electric Power Systems Research, 78(4): 626–633, 2008.

[141] Subramanian S, Anandhakumar R., Dynamic economic dispatch solution using composite cost function. International Review of Electrical Engineering, 5(4) Part B:1664–1669, 2010.

[142] He D-K, Wang F-L, Mao Z-Z., A hybrid genetic algorithm approach based on differential evolution for economic dispatch with valve-point effect. International Journal of Electrical Power and Energy Systems, 30(1):31–38, 2008.

[143] Noman N, Iba H., Differential evolution for economic load dispatch problems. Electric Power Systems Research, 78(8):1322–1331, 2008.

[144] Chiang C L., Genetic-based algorithm for power economic load dispatch. IET Generation, Transmission and Distribution, 1(2):261–269, 2007.

[145] Immanuel Selvakumar A, Thanushkodi K., A new particle swarm optimization solution to non-convex economic dispatch problems. IEEE Transactions on Power Systems, 22(1):42–51, 2007.

[146] Amjady N, Sharifzadeh H., Solution of non-convex economic dispatch problem considering valve loading effect by a new modified differential evolution algorithm. International Journal of Electrical Power & Energy Systems, 32(8):893–903, 2010.

[147] Lu H, Sriyanyong P, Song Y.H, Dillon T., Experimental study of a new hybrid PSO with mutation for economic dispatch with non-smooth cost function. International Journal of Electrical Power & Energy Systems, 32(9):921–935, 2010.

[148] Niknam T., A new fuzzy adaptive hybrid particle swarm optimization algorithm for non-linear, non-smooth and non-convex economic dispatch problem. Applied Energy, 87(1):327–339, 2010.

[149] Park J-B, Lee K-S, Shin J-R, Lee K.Y., A particle swarm optimization for economic dispatch with nonsmooth cost function. IEEE Transactions on Power Systems, 20(1):34–42, 2005.

[150] Pereira-Neto A, Unsihuay C, Saavedra O R., Efficient evolutionary strategy optimization procedure to solve the nonconvex economic dispatch problem with generator constraints. IEE Proceedings- Generation, Transmission and Distribution, 152(5): 653–660, 2005.

[151] Liu D, Cai Y., Taguchi method for solving the economic dispatch problem with nonsmooth cost functions. IEEE Transactions on Power Systems, 20(4):2006–2014, 2005.

[152] Amjady N, Nasiri-Rad H., Solution of nonconvex and nonsmooth economic dispatch by a new adaptive real coded genetic algorithm. Expert Systems with Applications, 37(7): 5239–524, 2010.

[153] Pothiya S, Ngamroo I, Kongprawechnon W., Ant colony optimisation for economic dispatch problem with non-smooth cost functions. Electrical Power and Energy Systems, 32(5): 478–487, 2010.

[154] Kaveha A., Talataharib S., Size optimization of space trusses using Big Bang-Big Crunch algorithm. Computers and Structures, 87: 1129-1140, 2009.

[155] Labbi Y., Attuos D.B., Environmental/economic power dispatch using a Hybrid Big Bang–Big Crunch optimization algorithm. International Journal of System Assurance Engineering and Management, 5(4):602-610, 2014.

[156] Z.-L. Giang, Particle swarm optimization to solving the economic dispatch considering the generator constraints. IEEE Trans. On Power system, 1187-2123, 2003.

[157] C. Jiejin, M. Xiaoqian, L. Lixiang and P.H. Peng, Chaotic particle swarm optimization for economic dispatch considering the generator constraints. Energy Conversion & Management, 645-53, 2007.

[158] S. Khamsawang and S. Jiriwibhakorn, Solving the Economic Dispatch Problem using Novel Particle Swarm Optimization. International Journal of Electrical and Electronics Engineering, 3:41-46, 2009.

[159] Cai J, Xiaoqian M, Qiong L, Lixiang L, Haipeng Peng D., A multi-objective chaotic particle swarm optimization for environmental/economic dispatch, Energy Conversion and Management, 50:1318–1325, 2009.

[160] Abido MA., A niched Pareto genetic algorithm for multiobjective environmental/economic dispatch. Electr Power Syst Res, 25:97–9, 2003.

[161] Farag A, Al-Baiyat S, Cheng T C, Economic load dispatch multiobjective optimization procedures using linear programming techniques. IEEE Trans. Power Syst., 10:731–738, 1995.

[162] Burns, R.M. and C.A. Gibson, Optimization of priority lists for a unit commitment program. Proc. of IEEE/Power Engineering Society Summer Meeting, Paper A 75, 453–1, 1975.

[163] Roy, P.K., Solution of unit commitment problem using gravitational search algorithm. International Journal of Electrical Power & Energy Systems, 53(2):85-94, 2013.

[164] L.L. Garver, Power generation scheduling by integer programming-development of theory. Power Apparatus and Systems, Part III. Transactions of the American Institute of Electrical Engineers, 81(3):730-734, Apr. 1962.

[165] Lowery, P., Generating Unit Commitment by Dynamic Programming. IEEE Trans. on Power Apparatus and Syst. IEEE Trans. on Power Apparatus and Systems, PAS-85(5):422-426, 1966.

[166] Snyder, W., L., Powell, H., David, Rayburn, John, C., Dynamic Programming Approach to Unit Commitment. IEEE Trans. Power Syst. IEEE Trans. on Power Systems, 2(2):339-348, 1987.

[167] Cohen, A.Y.M., A Branch-and-Bound Algorithm for Unit Commitment. IEEE Trans. on Power Apparatus and Syst. IEEE Trans. on Power Apparatus and Systems, PAS-102(2):444-451, 1983.

[168] Baptistella, L.F.B., Geromel, J. C., Decomposition approach to problem of unit commitment schedule for hydrothermal systems. Control Theory and Applications, IEE Proceedings, 127(6):250–258, 1980.

[169] Bard, J.F., Short-Term Scheduling of Thermal-Electric Generators Using Lagrangian Relaxation. Operations Research, 36(5):756-766, 1988.

[170] Zhuang, F., Galiana, F. D., Towards a more rigorous and practical unit commitment by Lagrangian relaxation. IEEE Trans. Power Syst. IEEE Transactions on Power Systems, 3(2):763-773, 1988.

[171] Zhuang, F., Galiana, F. D., Unit commitment by simulated annealing. IEEE Trans. Power Syst. IEEE Transactions on Power Systems, 5(1):311-318, 1990.

[172] Xiaomin, B., Shahidehpour, S.M., Erkeng, Y., Constrained unit commitment by using tabu search algorithm. in Proceedings of the International Conference on Electrical Engineering, 2:1088-1092, 1996.

[173] Orero, S.O. and M.R., Irving, A Genetic Algorithm Modelling Framework and Solution Technique for Short Term Optimal Hydrothermal Scheduling. IEEE Transactions On Power Systems PWRS, 13(2): 501-518, 1998.

[174] Lee, F.N., Short-term thermal unit commitment-a new method. IEEE Trans. Power Syst. IEEE Transactions on Power Systems, 3(2):421-428, 1988.

[175] Sheble, G.B., Fahd, G. N., Unit commitment literature synopsis. IEEE Trans. Power Syst. IEEE Transactions on Power Systems, 9(1):128-135, 1994.

[176] Tong, S.K.S.S.M.O.Z., A heuristic short-term unit commitment. IEEE Trans. Power Syst. IEEE Transactions on Power Systems, 6(3):1210-1216, 1991.

[177] Kaya, Y., Uyar, Murat and R. Tekin, A Novel Crossover Operator for Genetic Algorithms: Ring Crossover. Computing Research Repository Journal, arXiv:1105.0355 [cs.NE], May 2011.

[178] Sivanandam, S.N. and S.N. Deepa, Introduction to genetic algorithms, Springer: Berlin; New York, 2007.

[179] Holland John Henry, Adaptation in natural and artificial systems an introductory analysis with applications to biology, control, and artificial intelligence, Cambridge (Mass.); London: The MIT Press, 1992.

[180] V., S., Kumar, M. R., Mohan, Two Level Crossover Genetic Algorithm For Unit Commitment Problem. WSEAS transactions on computers, 2(3):554–559, 2003.

[181] Pavez-Lazo, B. and J. Soto-Cartes, A deterministic annular crossover genetic algorithm optimisation for the unit commitment problem. Expert Systems with Applications, 38(6):6523-6529, 2011.

[182] Grzegorz Dudek, Genetic algorithm with integer representation of unit start-up and shut-down times for the unit commitment problem. European Transactions on Electrical Power, 17(5):500-511, September 2007.

[183] Dang, C.L.M., A floating-point genetic algorithm for solving the unit commitment problem. European Journal of Operational Research, 181(3):1370-1395, 2007.

[184] Damousis, I.G., Bakirtzis, A.G., Dokopoulos, P.S., A solution to the unit-commitment problem using integer-coded genetic algorithm. IEEE Transactions on Power Systems, 19(2):1165 - 1172, 2004.

[185] Pappala, V.S., Erlich, I. A new approach for solving the unit commitment problem by adaptive particle swarm optimization. in IEEE Power and Energy Society General Meeting - Conversion and Delivery of Electrical Energy in the 21st Century. 20-24 July 2008. Pittsburgh, PA.

[186] Eldin, A.S., M.A.H. El-sayed, and H.K.M. Youssef. A two-stage genetic based technique for the Unit Commitment optimization problem. in 12th International Middle East Power System Conference, MEPCO. 2008.

[187] Wei Xiong, M.-J.L., Yuan-lin Cheng. An Improved Particle Swarm Optimization Algorithm for Unit Commitment. in International Conference on Intelligent Computation Technology and Automation (ICICTA) 2008.

[188] Chusanapiputt, S., Nualhong, D., Jantarang, S., Phoomvuthisarn, S. A solution to unit commitment problem using hybrid ant system/priority list method in IEEE 2nd International Power and Energy Conference, PECon. . 1-3 Dec. 2008 Johor Bahru.

[189] Juste, K.A., Kita, H., Tanaka, E. and J. Hasegawa, An Evolutionary Programming Solution to the Unit Commitment Problem. IEEE Transactions On Power Systems Pwrs, 14(4):1452-1459, 1999.

[190] Satoh, T., Nara, K., Maintenance scheduling by using simulated annealing method (for power plants). IEEE Trans. Power Syst. IEEE Transactions on Power Systems, 6(2):850-857, 1991.

[191] Cheng, C.P., C.W. Liu, and C.C. Liu, Power System Analysis, Computing, And Economics Committee - Unit Commitment by Lagrangian Relaxation and Genetic Algorithms. IEEE transactions on power systems : a publication of the Power Engineering Society., 15(2):707-714, 2000.

[192] Hosseini, S.H., Khodaei, A., Aminifar, F., A Novel Straightforward Unit Commitment Method for Large-Scale Power Systems. IEEE Transactions On Power Systems Pwrs, 22(4):2134-2143, 2007.

[193] Tokoro, K.-I., Masuda, Y., Nishino, H., Solving unit commitment problem by combining of continuous relaxation method and genetic algorithm. Annual Conference International Conference on Instrumentation Control Information, Proceedings of the SICE Annual Conference,3474-3478, 2008.

[194] David, E., Goldberg., Genetic Algorithms in Search, Optimization and Machine Learning. Reading, Mawss.: Addison Wesley, 1989.

[195] Vlahogianni, E.I., Karlaftis, M.G., Golias, J.C., Optimized and meta-optimized neural networks for short-term traffic flow prediction: A genetic approach. Transportation Research Part C: Emerging Technologies, 13(3):211–234, 2005.

[196] Reeves, C.R, Rome, J.E., Genetic Algorithms Principles and Perspectives. Kluwer Academic Publishers. Dordrecht, 2003.

[197] Kellegoz, T., Toklu, B., Wilson, J., Comparing efficiencies of genetic crossover operators for one machine total weighted tardiness problem. App. Math. and Computation, 199:590–598, 2008.

[198] Booker, L., Improving search in genetic algorithms, In Genetic Algorithms and Simulated Annealing. L. Davis (Ed.).Morgan Kaufmann Publishers, 1987.

[199] Kaya, M., The effects of two new crossover operators on genetic algorithm performance. Applied Soft Computing, 11:881–890, 2011.

[200] Orero, S.O, Irving, M.R., Large scale unit commitment using a hybrid genetic algorithm. Int. J. Elect. Power Energy Syst., 19(1):45–55, 1997.

[201] Swarup, K.S., Yamashiro, S., Unit commitment solution methodology using genetic algorithm. IEEE Transactions on Power Systems, 17(1):87–91, 2002.

[180] Kumar, V.S., Mohan, M.R., Two Level Crossover Genetic Algorithm For Unit Commitment Problem. WSEAS transactions on computers, 2(3):554–559, 2003.

[181] Boris Pavez-Lazo, Jessica Soto-Cartes., A deterministic annular crossover genetic algorithm optimisation for the unit commitment problem. Expert Syst. Appl., 38(6):6523–6529, 2011.

[202] Jorge, Valenzuela, Alice, E. Smith., A Seeded Memetic Algorithm for Large Unit Commitment Problems. Journal of Heuristics, 8(2):173–195, March 2002.

[203] Senjyu, T., Yamashiro, H., Uezato, K., and Funabashi, T., A unit commit-ment problem by using genetic algorithm based on characteristic classi-fication. inProc. IEEE/Power Eng. Soc. Winter Meet., 1:58–63, 2002.

[204] Ongsaku, W., and Petcharaks, N. Unit commitment by enhanced adaptive Lagrangian relaxation. IEEE Trans. Power Syst., 19(1):620–628, Feb. 2004.

[205] Salomon, R., Evolutionary algorithms and gradient search: similarities and differences. IEEE Transa Evol Comput, 2(2):45–55, 1997.

[206] Bilal Alatas, Uniform Big Bang–Chaotic Big Crunch optimization. Commun. Nonlinear. Sci. Numer. Simulat., 16:3696–3703, 2011.

[207] Yang, XS, Hosseinib, SSS, Gandomic, AH.. Firefly algorithm for solving nonconvex economic dispatch problems with valve loading effect. Appl Soft Comput, 12(3):1180–6, 2012.

[208] Malik, T.N., Asar, A., Wyne, M.F., Akhtar, S., A new hybrid approach for the solution of nonconvex economic dispatch problem with valve-point effects. Electric Power Systems Research, 80:1128–1136, 2010.

[209] Celal, Yasar, Serdar, Özyön., A new hybrid approach for nonconvex economic dispatch problem with valve-point effect, Energy, 36:5838–5845, 2011.

[210] Kumar, R., Sharma, D., Sadu, A., A hybrid multi-agent based particle swarm optimization algorithm for economic power dispatch. Int J Ele. Power Ene. Sys., (33):115–23, 2011.

[211] Amjady, N., Sharifzadeh, H., Solution of non-convex economic dispatch problem considering valve loading effect by a new modified differential evolution algorithm. Int J Elect Power Energy Syst, (32):893–903, 2010.

[212] Meng, K., Wang, H.G., Dong, Z., Wong, K.P., Quantum-inspired particle swarm optimization for valve-point economic load dispatch. IEEE Trans Power Syst, 25:215–22, 2010.

[213] Chaturvedi, K.T., Pandit, M., Srivastava, L., Particle swarm optimization with time varying acceleration coefficients for non-convex economic power dispatch. Int J Elect Power Energy Syst, 31:249–57, 2009.

[214] AL-Sumait, J.S., Sykulski, J.K., AL-Othman, AK.,. Solution of different types of economic load dispatch problems using a PS method. Elec Power Compos Syst, 36:250–65, 2008.

[215] Kirkpatrick, S., Gelatt, Jr., C.D., Vecchi, M.P., Optimization by simulated annealing. Science, 220:671–680, 1983.

[216] Niknam, T., Doagou, Mojarrad H., Zeinoddini, Meymand H., A novel H-PSO for economic dispatch with valve-point loading effects. Ener Convers Manage, 52:1800–1809, 2011.

[217] Vlachogiannis, J.G., Lee, K.Y., Economic load dispatch a comparative study on heuristic optimization techniques with an improved coordinated aggregation-based PSO. IEEE Trans Power Syst, 24:991–1001, 2009.

[218] Mohammadi-Ivatloo, B., Rabiee, A., Soroudi, A., Ehsan, M., Iteration PSO with time varying acceleration coefficients for solving non-convex economic dispatch problems. Electrical Power and Energy Systems, 42: 508–516, 2012.

[219] Colorni, A., Dorigo, M., Maniezzo, V., Distributed Optimization by Ant Colonies. Actes de la première conférence européenne sur la vie artificielle, Paris, France, Elsevier Publishing, 134–142, 1991.

[220] Mahor, A., Prasad, V., Rangnekar, S., Economic dispatch using particle swarm optimization: a review. Renew Sust Energy, 13(8):2134–2141, 2009.

[221] Dakuo, H., Fuli, W., Zhizhong, M., A hybrid genetic algorithm approach based on differential evolution for economic dispatch with valve-point effect.Electric Power and Energy Systems, 30, 31–38. 2008.

[222] John S. Gero, Vladimir Kazakov, A genetic engineering approach to genetic algorithms. EVOLUTIONARY COMPUTATION, 9:71-92, 2001.

[223] C.P. Cheng, C.W. Liu, C.C. Liu, Unit Commitment by lagrangian relaxation and genetic algorithms. IEEE Transactions on Power Systems, 15(2):707–714, 2000.

[224] Y. Tingfang, T.O. Ting, Methodological priority list for Unit Commitment Problem. In: International Conference on Computer Science and Software Engineering, CSSE, 1:176–179, 2008.

[225] Dilip Datta, Unit commitment problem with ramp rate constraint using a binary-real-coded genetic algorithm, Applied Soft Computing, 13:3873–3883, 2013.

[226] Simopoulos DN, Kavatza SD, Vournas CD., Unit commitment by an enhanced simulated annealing algorithm. IEEE Trans Power Syst, 21(1):68–76, 2006.

[227] Chung CY, Yu H, Wong KP. An advanced quantum-inspired evolutionary algorithm for unit commitment. IEEE Trans Power Syst, 26(2):847–54, 2006.

[228] Chandram K, Subrahmanyam N, Sydulu M., Unit commitment by improved pre-prepared power demand table and Muller method. Int J Electr Power Energy Syst, 33:106–14, 2011.

[229] Chakraborty S, Ito T, Senjyu T, Saber AY., Unit commitment strategy of thermal generators by using advanced fuzzy controlled binary particle swarm optimization algorithm. Int J Electr Power Energy Syst, 43(1):1072–80, 2012.

[230] Chandrasekaran K, Simon Sishaj P., Network and reliability constrained unit commitment problem using binary real coded firefly algorithm. Int J Electr Power Energy Syst, 43(1):921–32, 2012.

[231] R. Quan et al., Tighter relaxation method for unit commitment based on second-order cone programming and valid inequalities. Electrical Power and Energy Systems, 55:82–90, 2014.

[232] Jeong, Y.W., Park, J.B., Shin, J.R., Lee, K.Y., A thermal unit commitment approach using an improved quantum evolutionary algorithm. Electr. Power Compon. Syst., 37(7):770–786, 2009.

[233] Jeong, Y.W., Park, J.B., Jang, S.H., Lee, K.Y., A new quantum-inspired binary PSO: application to unit commitment problems for power systems. IEEE Trans. Power Syst., 25(3):1486–1495, 2002.

[234] Yuan, X., Su, A., Nie, H., Yuan, Y., Wang, L., Application of enhanced discrete differential evolution approach to unit commitment problem. Energy Convers. Manage., 50:2449–2456, 2009.

[235] Zhou Wu, Tommy W.S. Chow, Binary neighbourhood field optimisation for unit commitment problems. IET Gener. Transm. Distrib., 7(3) :298–308, 2013.

[236] Slimani Linda, Contribution à l'application de l'optimisation par des méthodes métaheuristiques à l'écoulement de puissance optimal dans un environnement de l'électricité dérégulé. PhD thesis, Batna University, 2009.

[237] EA Jasmin, Reinforcement Learning Approaches to Power System Scheduling. PhD thesis, Cochin University of Science and Technology, 2008.