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THEME

Fonctionnement Flexible, Optimal, et Intelligent des Réseaux Electriques en Appliquant des Techniques Hybrides.

Flexible, Optimal, and Intelligent Operation of Electrical Networks by Applying Hybrid Techniques.

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ملخص

على مدار السنوات الحالية، الطلب على الطاقة يزداد مع تطور التصنيع. العديد من وسائل الإدارة والتخطيط قد استخدمت. ومع ذلك ، هناك حاجة إلى اختبارات وتطورات إضافية لتحسين التشغيل والتحكم. يعد التدفق الأمثل للطاقة OPF والتوزيع والتوزيع الاقتصادي ED من المشكلات الأساسية التي يحلها مشغلو النظام من أجل تقليل التكاليف المرتبطة بالتشغيل الموثوق لشبكات الطاقة وما إلى ذلك, لخفض تكاليف الوقود والحفاظ على طاقة المولدات وفولتية العقدة ضمن حدود آمنة .

تتناول هذه الأطروحة مشكلتين رئيسيتين تواجههما بشكل شائع في دراسات تحليل النظام الكهربائي ، وهما: تدفق الطاقة الأمثل OPF وانبعاثات الطاقة المعتمدة على الانبعاثات الاقتصادية EED . يتم التعبير عن كلتا المشكلتين في شكل مشكلة تحسين مثلي مختلط مع أهداف مختلفة ، مثل تكلفة الوقود والانبعاثات وفقدان الاستطاعة الفعلية وتعزيز خصائص الجهد واستقرار الفولتية . التوتر ، وبعضها غير محدب وغير تفاضلية. يتم التعبير عن هذا الأخير كمشكلة تحسين متعددة الأهداف غير خطية ذات أهداف متناقضة وتخضع لقيود المساواة وعدم المساواة في كلتا الدراستين ، يولى اهتمام خاص للجوانب البيئية والاقتصادية لتوليد الطاقة الكهربائية. .

ومع ذلك ، يتم البحث عن حلول لكلتا المشكلتين من خلال تقنية هجينة متوازية ومتسلسلة مثل خوارزمية الكريل KHA وخوارزمية بحث الوقواق CS هذه الطريقة الهجينة هي تقنية تحسين حديثة تحظى حالياً باهتمام إضافي.

تم اختبار المشكلة الأولى على شبكات نماذج IEEE 30, IEEE 57, IEEE118 عقدة ، وتم اختبار المشكلة الثانية على شبكات 3 و 6 و 10 و 13 و 40 مولد للتحقق من فعالية التقنيات. المقترحة تتم مقارنة نتائج طرق تحسين هذه لمختلف مشكلات نظام الطاقة مع نتائج طرق التحسين الأخرى. تؤكد النتائج الجيدة للاستراتيجيات المقترحة على إمكانية استخدامها في أنظمة الطاقة العملية.

الكلمات المفتاحية : سريان الطاقة الأمثل, مشكلة التوزيع الاقتصادي والانبعاث , خوارزميه القطيع كريل, خوارزمية البحث الوقواق, ميتاهوريستيكية , تقنيات التحسين.

Abstract

Over the present years, with the development of industrialization, the demand for electricity has been rising. Different management and planning tools have been employed; however additional testing and development are necessary to make the best exploitation and control. The optimal Power Flow (OPF) and economic scheduling (ED) problems are the basic problems that system operators solve so as to decrease the costs related with reliable operating grids' power, so as to decrease fuel costs and maintain the power outputs of generators and bus voltages within their safety limits,

This thesis handle two major problems commonly encountered in studies related to the analysis of power systems, namely the optimal power Flow (OPF) and economic dispatch of emissions (EED). The first problem is expressed as a mixed integer optimization problem with different targets, such as fuel costs, emissions, active power losses, enhancement of voltage profile and voltage stability some of which are non-convex and non-differential nature. The latter is expressed as a nonlinear multi-objective optimization problem with conflicting goals and subject to constraints of equality and inequality. In the two surveys, special attention is given to the environmental and economic parts of electric power generation.

However solutions to the two problems are studied via hybrid parallel and series technique such as Krill Herd (KH) and Cuckoo Search (CS). This hybrid method is a modern meta-heuristic optimization technique which acquires additional attention lately.

The first problem has been tested on the network IEEE -30, IEEE -57 and IEEE-118 bus test systems, and the second problem has been tested on network 3, 6, 10, 13 and 40 generators to verify the efficiency of these proposed techniques. The results of these meta-heuristic optimization methods for different power system problems are compared with those of other optimization methods. The good results of the proposed strategies underscore their potential to be utilized in practical power systems.

Keywords: Optimal power flow; Economic emission load dispatch; krill herd algorithm; Cuckoo search algorithm; metaheuristics ; Optimization

Résumé

Au cours des années actuelles, avec le développement de l’industrialisation, la demande en électricité a augmenté. Différents outils de gestion et de planification ont été utilisés. Cependant, des tests et des développements supplémentaires sont nécessaires pour optimiser l’exploitation et le contrôle. L’écoulement de puissance optimal (OPF) et la répartition de l’économique de puissance (ED) sont des problèmes de base que résolvent les opérateurs de système afin de réduire les coûts liés à une exploitation fiable des réseaux de puissance et ainsi. Afin de réduire les coûts de carburant et maintenir la puissance des générateurs et des tensions de nœuds dans les limites de sécurité.

Cette thèse traite deux problèmes majeurs couramment rencontrés dans les études relatives à l'analyse des systèmes électriques, à savoir l’écoulement de puissance optimal (OPF) et la répartition économique émission de puissance tenant compte des émissions (EED). Les deux problèmes est exprimé sous la forme d’un problème d’optimisation mixte- entier avec différentes cibles, telles que le coût du carburant, les émissions, les pertes de puissance active, l’amélioration du profil de la tension et la stabilité de la tension, dont certaines sont de nature non convexe et non dérivable. Le dernier est exprimé sous la forme d'un problème d’optimisation multi-objectif non linéaire à objectifs contradictoires et soumis à des contraintes d'égalité et d'inégalité. Dans les deux études, une attention particulière est accordée aux aspects environnementaux et économiques de la production d’énergie électrique.

Cependant, les solutions aux deux problèmes sont étudiées via une technique hybride parallèle et en série telle que Krill Herd (KH) et Cuckoo Search (CS). Cette méthode hybride est une technique moderne d'optimisation méta-heuristique qui suscite actuellement une attention supplémentaire.

Le premier problème a été testé sur les réseaux modèles IEEE -30, IEEE -57 et IEEE-118 nœuds, et le deuxième problème a été testé sur les réseaux 3, 6, 10, 13 et 40 générateurs pour vérifier l'efficacité des techniques proposées. Les résultats de ces méthodes d'optimisation méta-heuristiques pour différents problèmes de système de puissance sont comparés à ceux d'autres méthodes d'optimisation. Les bons résultats des stratégies proposées soulignent leur potentiel d'utilisation dans des systèmes de puissance pratiques.

Mots-clés: Écoulement de Puissance Optimale; Algorithme Krill troupeau; répartition des économiques de puissance; Métaheuristiques; Optimisation.

Dedication

I dedicated this modest work to:

*My dear parents.

* My sisters and brothers.

* To all those who helped me, from near or far. Same with a simple word of encouragement

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List of symbols and abbreviations

P_i and Q_i represent the active and reactive power

g (x, u): set of inequality constraints

$h(x, u)$: set of equality constraints

P_{G_i} is the i-th active power bus generator

V_{G_i} is the voltage magnitude at i-th voltage controlled generator bus,

T_j is the j-th branch transformer tap,

Q_{C_k} is the shunt compensation at k-th bus.

N_G, N_C and N_T are the generators' number, transformers and shunt VAR compensators.

δ_i and δ_j is the voltage angles among bus i and bus j

Q_{Di} and P_{Di} are reactive and real load demands.

G_{ij} is the transfer conductance

B_{ij} is the susceptance among bus i and bus j

a_i ,b_i and c_i are the cost coefficient of the generator unit

α_i , β_i and γ_i are the emission function coefficients of the ith generating unit

N_i is the movement induced by other krill individuals

F_i is the foraging motion

D_i is the ith krill individuals' physical diffusion.

$N^{\max}$ is the upper induced velocity

ω_n is the inertia weight of the motion induced in the field [0, 1]

N_i^{old} is the end motion induced

α_i^{local} is the local effect provided by the neighbors

$\alpha_i^{t\arg et}$ is the target direction effect provided by the preferable krill individual.

K^{best} and K^{worst} are the preferable and worst fitness condition values of the krill individuals so far

C^{best} is the krill individual's effective coefficient having the preferable fitness to the individual of *ith* krill

V_f is the food search velocity

ω_f is the inertia weight of food search movement in the field [0, 1]

F^{old} is the last food search movement

β_i^{food} is attractive food and β_i^{best} is the effect of the preferable fitness condition of the ith krill so far

L_j is the local indicator of bus j

$\lambda_{L_{\max}}$, λ_E , λ_{VD} , λ_p are a weighting factors

PV, PQ Voltage-controlled bus and Load buses

OPF Optimal Power Flow

ED Economic Dispatch

PSO Particle Swarm Optimization

BF Bacterial Foraging

OPF-SC Optimal Power Flow with Safety Constraints

CEED Combined Economic Emission Dispatch

Vpe Valve point effect

NSS Novel Stochastic Search

NO_X Nitrogen Oxides, SO_X Sulphur Oxides and CO_X Carbon Oxides

MOEED Multi-Objective Economic Emission Dispatch

LP Linear Programming

NP Nonlinear Programming Technique

QP Quadratic Programming

IP Interior Point

CS Cuckoo Search

KH Krill Herd

CS-KHA hybrid Cuckoo Search and Krill Herd

KU Krill Updating

KA Krill Abandoning

Plosses active power losses

VD Voltage Deviation

L-max Voltage stability Index

CS-KHA^1 refers to the hybridization method on the parallel

CS-KHA ^{2} refers to the hybridization method on the series.

Chapter 1. Introduction

1.1 General

An interconnected power system illustrates an electrical network with many branches and nodes in which the transmission line usually forms a branche. In a power line, the nodes are called a "buses." On some buses, power is injected into the network, while in some other buses it is split by the system loads. Between the two, power will flow through the network meshes. A given set of loads can be is provided by a given generator set in an unlimited number of load flow.

Load flow (power flow) research includes the power system networks' solutions under the steady-state conditions. The solution is get by taking into account certain constraints of inequality applied to the bus voltage and reactive power of generators. The major information yielded from the load flow survey is the amplitude and phase angle of the voltage on every bus and the active and reactive power flowing in every line. Supposed that the system is balanced. This allows a single-phase illustration of the system [1].

The significant sides of the load flow analysis are as next:

1. The total quantity of active power in the network is evaluated from the generating station. The generation has to equal to the demand and losses of every moment, and the active power should be divided between generators at a unique rate so as to obtain optimal economic operation.
2. Since transmission links can only carry a certain quantity of power, it is important to guarantee that the link should not be also close to its stability or thermal boundaries to carry power.
3. It is needful to maintain the voltage levels of some buses within the range of precision tolerances. This can be reach by properly reactive power's scheduling.
4. If the power system is section of a greater pool, it should fulfill its power scheduling commitment by means of its "tie- lines" with adjacent systems.
5. The disturbances resulting from massive network failure can result in system failures whose effects can be minimized by appropriate power flow management strategies prior to failure [2].

6. Power flow analysis is very significant in the planning stages of modern networks or addition to present networks

1.2 Power flow

The Load flow analysis includes calculating the power flow and voltages of the transmission network for identified terminal or bus conditions. Either the bus self and mutual admittances constitute the bus admittance matrix Y_{bus} or the drive point and transfer impedances that constitute Z_{bus} can be employed to solve the power flow problem. Generally, the bus admittance matrix technique is choose for power flow analysis. The starting point for getting data is the system's a single line diagram. For every line, the numerical values of the Z-series impedance and the total line-charging of the admittance y are required to ensure that all elements of the n x n bus admittance matrix can be specified. The element Y_{ik} is:

$$\bar{Y}_{ik} = |Y_{ik}| \angle \theta_{ik} = |Y_{ik}| (\cos \theta_{ik} + j \sin \theta_{ik}) = G_{ik} + jB_{ik} \tag{1.1}$$

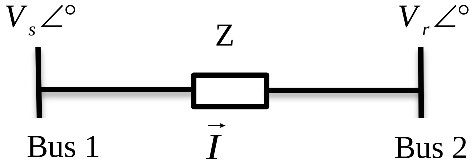

Figure 1.1. A simple two bus system.

Other basic information involves transformer ratings and impedances, shunt capacitance ratings and transformer tap Settings. Before each power flow study, we must assign known values to certain bus voltages and some power injections, as shown below.

The voltage at a model bus "i" of the system is offered in polar coordinates by,

$$\bar{V}_i = |V_i| \angle \delta_i = |V_i| (\cos \delta_i + j \sin \delta_i) \tag{1.2}$$

By changing the subscript from "*i*" to "*j*", a voltage similar to another bus "*j*" is written. According to the element Y_{ik} of Y_{bus}, the net current injected into the network at the bus ' *i* ' is given by summation [1].

$$I_i = Y_{i1}V_1 + Y_{i2}V_2 + \ldots + Y_{in}V_n = \sum_{k=1}^{n} Y_{ik}V_k \tag{1.3}$$

The power injected's complex conjugate at bus ' i ' is:

$$P_i - jQ_i = V_i^* \sum_{k=1}^{n} Y_{ik} V_k \tag{1.4}$$

Where P_i and Q_i represent the net active and reactive power bus ' i' that enters the network.

The Equation (1.4) can be formulated in the form polar coordinates

$$P_i = \sum_{k=1}^{n} |Y_{ik}||V_i||V_k| \cos\left(\theta_{ik} + \delta_k - \delta_i\right) \tag{1.5}$$

$$Q_i = -\sum_{k=1}^{n} |Y_{ik}||V_i||V_k| \sin\left(\theta_{ik} + \delta_k - \delta_i\right) \tag{1.6}$$

Equations (1.5) and (1.6) Form the power flow equations; they provide calculated values for the net active power P_i and reactive Q_i in the bus ' i ' into the network. Either P_{gi} represents the scheduled power generated on the bus "i" and P_{di} represents the demand for scheduled power of the load on this bus. Then $P_{i,sch} = P_{g_i} - P_{di}$ is the net scheduled power injected into the network on bus "i". By noting the computation value P_i by $P_{i,calc}$ result to the definition of the mismatch ΔP_i as a scheduled value $P_{i,sch}$ minus the computation value $P_{i,calc}$.

$$\Delta P_i = P_{i,sch} - P_{i,cal} = \left(P_{gi} - P_{di}\right) - P_{i,cal} \tag{1.7}$$

For reactive power at bus ‘i’,

$$\Delta Q_i = Q_{i,sch} - Q_{i,cal} = \left(Q_{gi} - Q_{di}\right) - Q_{i,cal} \tag{1.8}$$

Mismatches exist when the calculated values of P_i and Q_i are not consistent with the planned values. If the calculated values $P_{i,cal}$ and $Q_{i,cal}$ perfectly match the planned values $P_{i,sch}$ and $Q_{i,sch}$, the mismatch ΔP_i and ΔQ_i are equal to zero on the bus ' i ' and the equations (1.7) and (1.8) are named equilibrium equations of powers.

Four potentially undetermined quantities related with every bus ' i ' are P_i , Q_i , voltage angle δ_i , and voltage amplitude $|V_i|$.

The common practice of power flow research is to recognize three kinds of buses in the network. Specify four quantities in each bus ' i ' δ_i , $|V_i|$, P_i and Q_i , and calculate the remaining two. Select the specified quantity based on the following discussion:

1. Load buses (PQ bus)

At every non-generator bus, name a load bus, both the active and reactive power generation P_{g_i} and the Q_{g_i} are zero, and the active power demand P_{di} and reactive power demand Q_{di} drawn from the system by the load (negative inputs into the system) are recognized from historical report, load forecast, or measurement. In fact, in practice, only active power is usually known, and then reactive power is yielded based on a presumed power factor (for example, 0.85 or higher). A load bus "i" is often named the PQ bus for the scheduled values $P_{i,sch} = -P_{di}$ and $Q_{i,sch} = -Q_{di}$ are recognized and the mismatches ΔP_i and ΔQ_i can be outlined. To define that the two unknown quantities of the bus are δ_i and $|V_i|$.

2. Voltage-controlled bus (PV or Generator Bus)

Any bus in a system where the voltage magnitude remains constant is called a voltage controlled bus. A generator is related to each bus. The generation of megawatts can be controlled by adjusting the prime mover, and the amplitude of the voltage can be controlled by adjusting the excitation of the generator. Thus, in every generator bus ' i ' P_{gi} and $|V_i|$ is the identified and voltage angle δ_i is to determine the unknown quantity.

For evident reasons, a generator bus is often referred to as voltage controlled or PV buses. Some buses without generators may have voltage control capability.

This bus is also designated as a voltage controlled buses, where the active power generation is simply zero.

3. Slack Bus (Reference bus)

For appropriateness, bus 1 is almost always specified as a slack bus. The voltage angle of the slack bus is used as a reference bus voltage for whole other angles. The specific angle allocated to the slack bus voltage is not significant because the voltage angle differences define the calculated values of P_i and Q_i. The normal practice is to define $\delta_i = 0$. Mismatches are not outlined for the slack bus and voltage magnitude $|V_1|$ is identified as the other quantity known with $\delta = 0$.

1.3. Optimal power flow

Over the world, the electric power industry has attended a significant change to meet the rising necessarily of its consumers. The economic and reliable provide of electricity are the main necessarily of the consumers. The rising demand of electricity and the reduction energy sources have require the optimum use of obtainable resources. Scheduling of production resources available to meet load demand is a significant work of a power system operator to meet the economic necessarily of consumers. The economic operation is highly significant for any power system to realize the profits on the capital exploitation. As the price of fossil fuels continuously increasing and its availability is too reduction, these lead to the fossil fuels' conservation. This outline gives additional pressure to the electric power industry so as to achieve the maximum feasible fuel efficacy [3-5].

The Economic Dispatch (ED) is a significant optimization function in the operations of the electrical power system to allocate the generation among the committed units so that whole the constraints imposed are satisfied by decrease the operation fuel cost. Enhancements in the planning of unit products can lead to important cost savings. Therefore, the economic side of electric power generation itself required additional significant from the electric power industry.

The optimal Power flow (OPF) has been extensively applied in the power system operation and planning community since its developed by Carpentier in 1962 [6]. The OPF defines the optimum parameters for certain power system control variables by optimizing choice objective functions while satisfying a set of equality and inequality constraints for parameters data of loads and system parameters. The control variables involve the active powers of the generator, the transformer tap ratios, the generator bus voltages, and the reactive power generation of the shunt compensators. In comprehensive, the total cost of production is often used as the essential objective for optimal power flow problems. Therefore, the other objectives, such as decrease of network loss, the voltage stability enhancement and voltage profile improving can as well as be involved, as it has become progressively simple to formulate and solve convoluted extensively problems with the development in computing technologies. The equality constraints are the power flow equilibrium equations, whereas the inequality constraints are the boundaries on the control variables and the operating boundaries of the power system dependent variables. OPF is a non-linear and non-convex multimodal optimization problem on an extensively with discrete and continuous control variables. The presence of nonlinear power flow constraints creates the problem non-convex even in the discrete control variables' absence [7].

1.4. A review on optimal power flow

The optimal Power Flow (OPF) problem was one of the most large-scale discussed topics in the power system. The goal of the optimal power flow is to decrease the cost of the whole system with the equality and inequality constraints' satisfaction.

Depending to the objective functions and constraints selected, there are various mathematical formulations for the OPF problem. They can be widely described as follows:

The optimal power flow technique is solved with control variable like real and reactive power and transformer ratio to decrease the instantaneous costs or losses by Dommel & Tinney (1968) [8]. The constraints applied in this literature are reactive sources, load voltages and tie line power angles. This is solved used the gradient method and the Newton method. Several derivations are obtainable in this literature to resolve the optimal power flow. Sasson (1969) deliberated about the lowest loss and economic dispatching problem solved employ non-linear programming solutions [9]. As the optimal power flow technique is based on the solution of the essential power flow, Peterson et al (1971) Makes a quick and accurate technique to solve the power flow [10]. The problem formulation and solution on the outage condition with optimal power flow has been presented by Alsac & Stott (1974) [11]. Wherefore the contingency analysis is done with whole the other security and voltage constraints. Introduced a new optimization algorithm, which optimizes the considerable system given by Burchett et al. (1982) [12]. In this, large problem is divided into small sub-problem to treat the largest system test. And a comparison is produced between the steepest suitable and quasi Newton approach.

Sun et al (1984) [13] meets some test with the optimal power flow technique with Newton method. This technique gives an optimal solution to the problem in any dimension. It is building on the controls' number or binding inequalities. There are some deficiency in the techniques of optimal power flow solution, they are given in the literature Tinney et al (1988) [14]. And without considering these deficiencies the problem of optimal power flow will not be more practical. Dias & EL-Hawary (1991) [15] has achieved a study of load modeling in security constrained OPF. When there is an implication of the security constraints there is a variation in the load demand because of the cost changes. And it is specified that there is an influence of tap changing transformer in this effect. Introduced the quadratic interior point method in optimal power flow by Momoh et al [16] (1994). This method produces a global optimal solution by determining the initial value of the problem. Huneault & Galiana (1991) [17] carried out a study on the optimal power flow with nearly 300 literatures with the technique of solution and its popularity.

A reactive power control based on fuzzy was presented by Abdul-Rahman & Shahidehpour [18] (1993). The objective functions and constraints are made by fuzzy. And no need to reverse the Jacobian matrix in this technique as with whole the other regular constraints are applied. The Unit commitment constraints are utilized in the optimum power flow and the economic dispatch constraints are utilized in the optimal power flow for the resource scheduling problem precisely given in 1996 [19]. In 1997 Momoh et al [20] presented some challenge faced by the optimal power flow. It is disconnected by a planning perspective and an extended implementation of the optimal power flow. Mean area theory is carry out for the optimal power flow technique including the continuous and discrete variables. This technique solves the OPF in an exact way. And annealing procedure is too utilized to obtain the global optimal results. OPF is solved with both the rectangular and polar form in 1998 [21]. Employed the interior point technique, the rectangular form is solved. So it brings with matrix solutions and predictor corrector can be applied to solve the dimensionality problem. Solved the OPF's interior point nonlinear programming technique by Wei et al. (1998) [22]. Because of its fast performance and robustness, it can be utilized for great bus systems.

In 1998, a literature review of the optimal power flow was carried out until the year 1993 for the last three decades [23, 24]. The categories such as quadratic programming, nonlinear programming, mixed integer programming, Newton-based solutions and interior point technique linear programming concerning papers are taken in account for study. In the aspect II, literature linear programming category, Newton Raphson method category, quadratic programming category and mixture of linear programming and interior point category analysis are reviewed. A novel unlimited point algorithm, whose details with Kuhn-Tucker optimality conditions is acceptable for solutions. Because of its easy transformation variables becomes unbounded. Momoh et al used an improved interior point method for solving the optimal power flow. This technique gives better speed, convergence and accuracy. Solves an evolutionary algorithm based OPF by Yuryevich (1999) [25]. Optimal dispatch of generation was offered by Saadat in his book (1999) [26]. It provides a clear performance of the Lagrange multiplier method of solving the optimal dispatch of generation with the lambda-iteration technique. This method has less susceptible to the initial points.

Gan et al (2000) [27] utilizes stability-constrained optimal power flow. As the system's stability is significant, this was considered a constraint in this literature. An efficient and reliable evolutionary-based approach to solve the optimal power flow problem was offered by Abido et al (2002) [28]. The suggested technique uses a Particle Swarm Optimization (PSO) method for optimal settings of OPF problem control variables. Integration of PSO as a derivative-free optimization method in solving OPF problem importantly relieves the suppositions imposed on the optimized objective functions. The PSO method has a so small procedure and the update of state variables is too an easy equation. The results of the suggested technique were compared with those recently reported in the literature. The results are favorable and demonstration the efficiency and robustness of the suggested technique.

Suggested two new techniques for solving the OPF is applied they are graph-method based decomposition method, which decreases the great number of projection problem in to small divisions, they are presented by Lin Chi-Hsin et al (2002)[29]. This following method is an active-set strategy based DT technique, which can efficiently solve the medium-dimension projection sub-problems. And Bakirtzis et al (2002) [30] present an enhanced genetic algorithm for solving the OPF problem. This solves control variable of both discrete and continuous. Solves the primal dual techniques employed in the optimal power flow presented by Jabr et al (2002) [31] . This technique improves the convergence characteristics. Abido (2003) [32] offers other search technique named Tabu search technique used to resolve OPF. This technique improves the solution because of non-use of derived technique.

The formulated OPF problem employ a quasi-newton method iterated with the Newton-Raphson load flow module given by Tarek Bouktir & Mohamed Belkacemi (2003)[33] . A special matrix category is used to treate whole the system matrices where inputed and produced data can communicate with the OPF calculate modules via an object-oriented graphical employed interface and through a database object-oriented. Makes comparison between five evolutionary-based optimization algorithms presented by Elbeltagi et al (2005) [34]. The techniques used are particle swarms, genetic algorithms, memetic algorithms, shuffled frog leaping and ant-colony systems. William has suggested the complementary constraints to model the relationship among the base, or existing, operating point and the greatest loading in the power system.

Dynamic constrained optimal power flow was offered by Yan Xia & Ka Wing (2006) [35]. This modificatied the boundless constraint to limited constraint. The standard limited programming solves the OPF problem. Initialization procedure for optimal power flow solved with genetic algorithm was employed by Todorovski (2006)[36] . Suggested the hybridization of genetic algorithm with the interior point technique for optimal reactive power flow was presented by Wei et al (2006) [37] .

Some computational problems in optimal power flow in deregulated electricity market were suggested by Wang et al (2007) [38]. Yumbla et al (2008) [39] have solved the optimal power flow with security constraints applied particle swarm optimization techniques.

A new optimum power flow based on a hybrid current flow was suggested by Whei-min et al (2008) [40]. The predictor-corrector interior point method was used to solve the problem. The differential evolution algorithm was applied to solve the transient stability constrained optimal power flow suggests by Cai (2008) [41]. The formulation of optimal power flow with conic quadratic formulation was changed by Jabr (2008) [42]. Optimal reactive power flow control was solved by shuffled frog leap algorithm and compared the efficiency with genetic algorithm and particle swarm optimization suggested by Qingzheng (2009) [43]. An optimization of artificial bee colonies is applied to solve the optimum power flow used in 2010 [44]. Another optimization method is artificial bee colony optimization, is preferable between the other swarm based methods. A decomposition of security constrained (OPF) was offered by Yuan & McCalley (2008) [45]. Decrease the CPU timing by employing the decrease space interior point method for transient stability constrained OPF problem was presented by Quanyuan et al (2010) [46] . Used the harmony search method to optimal power flow and compared with particle swarm optimization method was presented by Nampetch et al (2013) [47].

Quanyuan Jiang et al (2010) [46], carry out an automatic differentiation in interior point OPF which has the potential to in online operating power system's environment .

In (2012) Amjady [48] , a new solution technique is suggested, which is an improved version of bacterial foraging (BF) method, used for the optimal Power Flow with safety constraints (OPF-SC) problems. OPFSC is a problem of optimizing nonlinear programming with a complex discontinuous solution space. Younes & Khodja (2012) [49] carry out a method based on a harmonic search algorithm for optimal power flow, compared to the genetic algorithm. In (2013) [50], artificial bee colony algorithm for solving optimal power flow problem was suggested by Loung et al. And he compares it with the methods recently used to solve it. Arul et al. (2014) [51] have offered a self-adaptive differential Harmony search algorithm for solving an optimal power flow with emission reduce. Raha et al (2014) [52] has offered the optimal reactive power dispatch based on the cuckoo search algorithm. An optimal power flow solution to problem applied a chaotic self-adaptive differential harmony search algorithm was offered by Arul et al. (2015) [53]. The results yielded by the suggested technique are better than the results yielded by differential and harmony search, chaotic differential and harmony search, internal point method and other algorithms described in the literature of point view solution quality and standard deviation of generation cost. In whence of convergence speed and calculation time, the suggested technique is better than differential harmony search and chaotic differential harmony search algorithms.

Thus, the papers examined shows that the optimal power flow has resulted in many changes in its objective functions and resolution techniques. However, there are research gaps, and there is no article to discuss about the efficiency of different evolutionary techniques applied to solve OPF.

It can be clearly seen from the literature review that many techniques have been suggested in the past, and many of them have been efficiently used in the optimal power flow. Because the solution surface of the optimal power flow problem is non-monotonous, the traditional techniques are very sensitive to the starting point, and many times it is either obtain trapped to local optima or diverge altogether. So as to achieve the assured convergence with the preferable quality solution, the biological inspiration optimization methods has been successfully applied to a variety of engineering applications.

1.5.Optimal Economic Dispatch

The significant of optimal economic dispatch begins with the time when two or more generating units are committed to meeting the load demand of the power system, and their total generating capacity exceeds the system demand. The generators' economic scheduling is designed to always ensure the best combination of generators connected to the system to meet load demand. This includes reduce fuel costs, line losses, and so on. The fundamental purpose of economic dispatch is to schedule the output of online fossil fuel generating units in order to meet the system load demand at the lowest cost.

The classical ED needs the curve of the input-output characteristics (millions of Btu per hour against MW) of the generating units. These additional heat rates of the units have to be a monotonous rising, smooth, convex and convex curve. In fact, the unit incremental thermal rate curve does not exhibit the monotonous increasing properties required by the traditional ED problem. Current power systems are extremely complex and their operations unpredictable.

The essential objective of the traditional electric power generation is to plan the outputs of the generating units engaged in order to meet the load demand with a minimum operating cost, while satisfying the constraints in Equality and inequality of the system described in Wood and Wollenberg (1996)[54].

Moreover, due to the growing awareness of environmental pollution, the limitation of polluant emissions in fossil-fuel-fired power plants becomes a vital problem for the dispatching of economic power. The economic power dispatch of traditional cannot meet the environmental protection necessities, as it only take into account the reduction of the total fuel cost.

The multi-objective power generation dispatch in power systems sees economic and emissions impacts as competitive goals, which requires some feasible compromise between objectives to achieve the best solution. This formulates the problem of the Combined Economic Emission Dispatch (CEED) with the objective of dispatch electrical power, taking into account both economic and environmental concerns.

Nevertheless, the actual ED must consider prohibited operating zones, ramp rate limits, valve point effects and multiple fuel options to ensure the completeness for the ED formulation. The resultant ED is a non-convex optimization problem, which is the most problematic and cannot be solved by conventional techniques.

1.6 A review on economic dispatch

Over the past 50 years, much research has been described on the ED problem. Depending on the complexity take into account, different objective functions and different solution techniques for the ED problem have been considered. For this suggested work, only a few objectives and techniques for the resolution of the significant literature, directly to the current work, are taken into account. Literature study has been offered on the basis of the following subjects [55].

1.6.1 Conventional Economic Dispatch

The different literature taking into account the convex nature of fuel cost reduction as the objective of the economic dispatch problem are discussed next.

A new technique for optimizing the active and reactive power dispatch for the economical operation of an electrical system has been offered by Lee et al (1985) [56].

This technique has essentially coupled the three modules like the optimal dispatch of the real power, optimum allocation of the reactive power and lastly with the load flow module. To solve this optimization problem, the gradient projection technique was introduced.

Chowdhury and Rahman (1990) [57] offered a general survey of papers and reports addressing different aspects of the ED problem. The period covered covers the period from 1977 to 1988. This survey provides a clear picture of what is available. Researchers in the field of ED can therefore identify problems and seek solutions.

In (1995) Farag et al [58], a new technique and algorithm based on linear programming techniques is described to obtain the best shift in ED problem related to contingency state or overload in the power system operation and planning phase under different objectives like economy, reliability and environmental conditions.

Conventional economic dispatch methods include the use of an advanced calculation method based on the Lagrangian function. The Lagrangian function is added to the constraint function and is too multiplied by the objective function through an unknown constant variable. Wood and Wollenberg (1996)[59] outlined many traditional methods, like gradients, Newton, linear programming and interior points, utilized to solve this well behaved formulation.

Song and Chou (1997) [60] formulated the traditional problem of ED with the quadratic form of the fuel cost function as a goal and solved it using the lambda iteration method with the help of advanced engineered conditioning genetic method.

A detailed account of the articles published after 1990, the year that saw the beginning of major changes in the organization of the power system given by Ciornei and Kyriakides (2012) [61]. Over the past 20 years, based on more than 150 publications, a comprehensive survey of mathematical formulas and a general background on methods, analysis and development in the field of economic dispatching have been proposed. The most concrete's database exam systems used in the literature is too provided to exam various techniques of economic dispatch methodologies.

1.6.2 Non-convex Economic Dispatch

Several of the preceding researchers examined the non-convex form of objective functions by integrating a valve point effect and multiple fuel options as well as a fuel cost function. The literature on non-convex ED is discussed follows.

To model the effects of valve points, a repetitive rectified sine contribution is added to the input-output equation of Walters and Sheble (1993) [62], which explains the multi-model solution space in the ED problem created by the valve point effect.

A traditional evolutionary programming technique for the problem of ED with piecewise quadratic cost function and the results are compared with Hopfield neural network method suggested by Jayabarathi and Sadasivam (2000) [63]. Both Park et al. (2005) [64] and Chiang (2005) [65] have began modeling realistic ED problems by taking into account valve point effects and a multiple fuels, which are present in real power systems at the same time.

Selvakumar and Thanushkodi (2007) [66] take into account the ED problem as a non-convex optimization problem by involving the practical operating conditions like valve point effect, prohibited operating zones and generation ramp rate limits, multiple fuels and prohibited operating zones.

Coelho and Mariani (2008, 2010) [67,68] and Amjady & sharizadeh (2010) [69] have take into consideration the valve point effect by introducing sinusoidal function in the quadratic fuel cost function. Formulated the convex and non-convex ED problems by taking into account the valve point effect and multiple fuel options were given by Bhattacharya and Chattopadhyay (2010) [70]. Khamsawang and Jiriwibhakorn (2010) [71] developed ED problems with 3 kinds of fuel cost functions, like ED with Valve point effect, ED with valve point effect and multiple fuels, and ED, which prohibited operating zones.

Tsai et al (2011) [72] have suggested the Novel Stochastic Search (NSS) method and Cai et al (2012) [73] have suggested a hybrid of chaotic Particle Swarm Optimization (PSO) and sequential quadratic programming based technique and both solved the non-convex ED problem. Tsai et al (2011) [72],The spread of the yielded optimal solution by the proposed algorithm has also been analyzed.

1.6.3 Economic Emission Dispatch

This section presents researchers who deal with environmental constraints while reducing the fuel cost.

A model is proposed to accurately estimating fuel costs and emissions with the help of modern probabilistic production costing techniques given by Heslin and Hobbs (1989) [74]. The weighted technique is applied to create a single objective by summing multiple targets.

The CEED problem is solved by stochastic method, which takes into consideration the uncertainty in the system cost and load demand's nature offered by Dhillon et al (1993) [75]. The weighted min-max technique is used to get non-inferior solutions of the multi-objective ED problem.

Ramanathan in (1994) [76] an effective emission constraint dispatch technique is suggested, which reduces operating costs and meets emission constraints. This paper has suggested two techniques. In the first technique, an effective method is developed to add emission constraints to the ED's traditional problem and to produce a fast convergence to the Kuhn-Tucker conditions. In the second technique, partial closed-form solutions are applied to obtain the Kuhn-Tucker conditions.

Talaq et al. (1994) [77] summarize the work carried out in the field of Economic Dispatch of the environment (EED). The summary involves many methods to reduce emissions in the atmosphere because of electric power generation.

On the basis of amendments of 1990 to the clean air act, Lamont and Obessis (1995) [78] renewed the focus on emission dispatching strategies and offered a set of dispatching algorithms as well as solution algorithms. Among them, Lamont and Obessis (1995) [78] have suggested a strategy to decrease total operating costs and estimate sulphur dioxide emissions permits under the 1990 amendment to the clean air act. It too proposes a new emission dispatch solution technique to obtain the lowest cost solution by reducing the generating units with the highest ratio of incremental emissions to incremental costs.

A comprehensive framework for modelling and assessing the economic impact of environmental dispatching and fuel switching proposed by Srinivasan and Tettamanzi (1997) [79]. The heuristic guided evolutionary techniques have been applied to solve the suggested ED model.

Solved the problem on EDD using -constraint techniques to generate non-inferior solutions and the compromise function between conflicting targets was given by Dhillon and Kothari (2000) [80].A method of trade off the surrogate value is too used to get the solution with the interaction of the decision maker.

Huang and Huang (2003) [81] have reported a new method that combines abductive reasoning networks with order preference methods to achieve real-time EED and optimal compromise solutions by similarity to the ideal solution decision method. The exam results show that this method is superior to the artificial neural network technique.

The price penalty factor to transform the problem of the EED to two goals into a single-objective CEED problem was presented by Selvakumar et al (2003) [82] and Kumarappan & Mohan (2004). A modified of penalty factor method to transform the two-objective CEED problem into a single-objective CEED problem was suggested by Venkatesh et al (2003) [83]. Alrashidi and El-Hawary (2006) [84] have offered compromise solutions to the multi-objective EED problem by transforming it into a single-objective EED problem employing the weight factor or utility factor.

Formulated the problem of dispatch loads multiple-criteria as an EED problem with a single-objective scalar optimization with weighting technique was offered by Singh et al. (2006) [85]. The fuel costs and atmospheric polluants caused by fossil fuel thermal generator units, like NO_X , SO_X and CO_X are taken into account to be four various objectives. Singh et al. (2006) [85] have fundamentally developed a methodology for calculating the best compromised solution by evaluating weights for every objective.

Bharathi et al (2007) [86] have formulated the bi-objective EED problem as single objective CEED with the help of price penalty factor approach. A solution methodology with the best weight pattern approach to optimize active and reactive power in power systems is suggested by Singh & Dhillon (2008) [87].

Hemamalini and Simon (2008) [88] using PSO have solved the problem of CEED as a single-objective problem with the help of weighted sum technique. Linear weight factor has been assigned for various targets depending on its significance.

Modelled multi-Objective problem of CEED as a single objective problem of CEED by integrating compromise factors and price penalty factors while adding the cost and emission objectives was given by Hota et al (2010) [89], Chatterjee et al (2012) [90] .

Güvenç (2012) [91] has too applied the price penalty method to transform the two-objective CEED problem into a single objective problem of CEED. Although the fuel cost function is taken into account in the CEED problem, the valve point effect is integrated. Solved the problem of EED as a single-objective optimization problem applied weighted sum technique was given by Özyön et al (2012) [92].

1.6.4 Multi-objective Economic Dispatch

Several researchers have suggested the problem of multi-objective economic dispatch by taking into account several contradictory objectives and have too offered optimal Pareto solutions instead of a single optimal solution.

Formulated the optimal load flow problem as a multi-objective optimization problem and were solved by the ε-constraint technique to get a set of non-inferiority solutions among the different objectives such as economy, reliability and minimum emission was offered Yokoyama et al. (1988) [93].

In (2006 and 2009) [94,95], Abido has formulated the fundamental problem of EED in the form of a non-linear constrained multi-objective environmental Economic Dispatch problem in which fuel cost and environmental impact are handled as competing objectives.

Also formulated the problem of EED as a multi-objective problem , with fuel cost and emission constituting conflicting objectives was given by Ah King (2003, 2005) [96]. He has considered three conflicting objectives, like fuel cost, NO_X and emissions and SO_X emissions.

Zhuang and Cai Guo-wei (2009)[97] have build the EED problem into a multi-objective model of power generation dispatch based on ideal point technique in target programming . Gong et al. (2010)[98] and Basu (2011)[99] have solved the highly constrained problem of EED as MOEED problem with conflicting objectives.

Sivasubramani and Swarup (2011)[100] have treated the MOEED problem with two competing objectives, like the quadratic form of the fuel cost function and the emission function with an exponential term.

Javad and Ghasemi (2012)[101] have formulated the MOEED problem as a non-linear constrained multi-objective problem with three competing objectives like fuel costs, emissions and system losses.

1.7. Traditional optimization techniques for optimal power flow

The traditional techniques were based on linearized objective functions and these techniques apply gradient-based sensitivity and optimization methods. The traditional techniques that have been used for the OPF problem are presented as follows.

1.7.1 Linear Programming technique

Linear programming (LP)-based technique is applied to linearize nonlinear power system optimization problems. This technique is reliable and has a perfect convergence characteristic, but the major flaw is that it could be trapped in the local minima. In addition, errors might appear, particularly in constraints, because of rounding by digital computers [102–104].

1.7.2 Nonlinear Programming technique

The Nonlinear Programming technique (NP) is more precise compared to linear programs where it can be utilized to non-linear objective functions and constraints.

The techniques of NP are based on the reduced gradient technique using the Lagrange multiplier or employ the optimization method of the penalty function. In this technique, the first partial derivatives of the equations (the reduced gradient) make it possible to select a search direction in the iterative procedure. The advantages of this technique are that it can be used in a large-scale system, while some drawbacks of this technique are that certain components [105–109].

1.7.3 Quadratic Programming technique

The quadratic programming (QP) can be take into account a special form of nonlinear programming technique where the objective function is quadratic, and the constraints are in linear form. This technique does not need the determination of the stages of the gradient. The solution yielded applied the QP technique is more precise compared than LP and NP and can be utilized in bad conditions. It has a fast convergence characteristic [110, 111].

1.7.4 Newton’s technique

Newton's technique is commonly applied in power flow problems based on the creation of the Lagrangian or decomposition method by applying second-order partial derivatives (the Hessian). The advantages of the Newton technique are that it can be utilized to various optimal power flow problems, that it has quick convergence characteristics and that it can effectively manage the constraints of inequality. The drawback of Newton's technique is that its convergence characteristics are so sensitive to the initial condition [112–115].

1.7.5 Interior Point technique

Interior point (IP) technique is generally applied to major problems and has been used to solve the optimal power problem. Nevertheless, the results yielded applied the IP result are better and require less iteration than LP, and can be trapped in local minima [116, 117].

1.8. Current optimization techniques for optimal power flow

The OPF problem is a multimodal, non-convex and nonlinear problem; therefore, the application of traditional techniques is not always appropriate and cannot ensure a global solution. In order to overcome the shortages of traditional techniques, many heuristic optimization methods have been developed to solve the OPF problem.

The benefits of new optimization methods can be summarized as next:

(1) These techniques can be using in small and great scale systems.

(2) High reliability to achieve optimum solutions.

(3) These techniques seldom suffer from stagnation or are trapped in local minima solutions.

(4) These techniques converge rapidly towards the optimal solution compared to traditional techniques.

In this section, we propose a comprehensive study of the implementation of the recent heuristics (non-deterministic) optimization methods for optimal power flow.

The heuristic optimization methods used for OPF problem can be categorized based on inspirational techniques as next:

1.8.1 Swarm and Bio-inspired Optimization Techniques

Nature-inspired and bio-inspired optimization methods are inspired by the movement and search conduct of swarms of animals or birds for food sources. The nature-inspired methods that have been utilized to the OPF problem [118-121].

1.8.2 Human-Inspired Optimization Techniques

Various optimization methods mimic human conduct, particularly in thinking or decision making. The human-inspired methods have been used to solve the OPF problem [122-124].

1.8.3 Physics-Inspired Optimization Techniques

Physics-inspired techniques are designed from in laws of physics or natural phenomena in space. The OPF optimization techniques apply physics heuristics [125-127].

1.8.4 Evolutionary-Inspired Optimization Techniques

The evolutionary optimization techniques are derived from the mechanics of natural chosen and genetics or living organisms or creatures. The evolutionary-based optimization methods have been used for the OPF problem [128-130].

1.8.5 Hybrid optimization techniques

Optimization methods continue to grow in significance because of its wide range of applications and therefore become an active research area. Despite of the landmark favorable outcome of deterministic and non-deterministic optimization methods usually and in the OPF aspect in particular, there are still some inherent shortcomings in every of these methods. This leads to a quest for hybrid optimization method that combines two or more methods into one method. Such that the benefits of every can be used to strengthen the others or to overcome their drawbacks. Important enhancements like computational time, convergence properties, and the quality of solution or the robustness of the parameters for each individual technique are achievable [131]. The hybridization could be:

1-Deterministic technique incorporated: Examples of this applicable to OPF are quasi – Newton incorporated with the Sequential Quadratic Programming (SQP) [132], Benders Decomposition incorporated Interior Point Method (IPMS)[133], Lagrangian Relaxation and Newton’s method incorporated Interior Point Method (IPMS) [134], linear programming (IP)and quadratic programming (QP)[135] , Linear Programming (LP) and Interior Point Methods (IPMS)[136]. etc.

2- Deterministic and non-deterministic incorporated: Examples of this as applicable to different form of OPF are Simulated Annealing (SA) incorporated with Newton's method [137] , incorporated linear Interior Point Method (IPM) with chaotic particle swarm optimization (PSO) [138] Newton's method incorporated with particle swarm optimization (PSO) [139] , improved evolutionary programming (IEP) and incorporated with the non-linear interior point (IP)[140], incorporated Genetic algorithm (GA) with interior point method(IPM) [141] ,etc.

3- Non - deterministic techniques incorporated: Differential Evolution (DE) incorporated with other meta-heuristics [142]; particle swarm optimization (PSO) incorporated with Simulated Annealing (SA) [143]; incorporated DE and Simulated Annealing (SA) [144], incorporated Tabu Search (TS) and Algorithm Genetic (GA) [145], incorporated Tabu Search (TS) and quasi-Newton method (QN) [145], incorporated imperialist competitive algorithm (ICA) and teaching learning algorithm (TLA) [146], etc.

Organization of thesis

Chapter 1: In particular, it provides an Introduction of the research field of optimal power flow, traditional and intelligent optimization techniques, and also mainly introduces the load dispatching research objectives and author's contribution in the field of research.

Chapter 2: This chapter mainly describes formulation of optimal power flow problem and economic dispatch problem.

Chapter 3: gives a general explains of hybrid meta-heuristics algorithms in power systems, and we in short review the main features of Meta-heuristics methods, focusing applied in this thesis, like both hybrid parallel and series CSKHA algorithm.

Chapter 4: deals with the application of hybrid algorithms to solve optimal power flow (OPF) problem. The suggested methods will be tested with IEEE 30-Bus system, IEEE 57-Bus system and IEEE 118-Bus system The results will discuss in detail the different with a single objective and multi-objective cases related to this work.

Chapter 5: explain the application of hybrid parallel and series CSKHA algorithm to solve both economic dispatch (ED) and economic emission dispatch (EED). The suggested technique is applied to 3, 6, 10, 13 and 40 generators.

1.9. Conclusion

This chapter describes the survey concerning the Optimal Power Flow (OPF) problem and Economic Load Dispatch (ELD). Hence, this chapter reported the following:

-The general offer of power flow importance and track the of time development of years in the field of power flow trend research.

-The traditional techniques that have been used to solve OPF and ELD problems, involve the advantages and drawbacks of these techniques.

-The new optimization methods that have been utilized to OPF and ELD. In addition, modern optimization techniques have been classified based on inspirational techniques like evolution, human, natural, biological and physical inspired methods.

From the above detailed literature review on OPF and ELD, it is important that many deterministic and stochastic optimization methods have been used to solve OPF and ELD problems. Furthermore the traditional deterministic mathematical optimization methods are complex and leads to high computational burden for large scale systems, and for stochastic techniques the great number of iterations leads to a very great computation time.

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Chapter 2: Problem formulation

2.1 Optimal power flow formulation (OPF)

The OPF problem aims at finding the optimal setting of control variables by minimizing/maximizing a predefined objective function while satisfying a set of equality and inequality constraints. OPF considering the operating limit of the system, it can be defined as a nonlinear constrained optimization problem [1].

Minimize: $f\ (x,u)$ (2.1)

Subject to:

$$\begin{aligned} h(x,u) &= 0 \\ g\ (x,u) &\leq 0 \end{aligned} \tag{2.2}$$

where, u is the independent variable or vector control, x is the dependent variables or vector of state. $f\ (x,u)$ Objective functions of OPF, g $(x,\ u)$: set of inequality constraints, $h(x,\ u)$: set of equality constraints.

The control variables in constraints of inequality are self-limiting. The optimization algorithm selects a viable value for each such variable within the defined scope. Effective techniques for dealing with inequality constraints related to state or dependent variables will be discussed in chapter 4.

-Objective functions of OPF

-Minimization of fuel cost

- Minimization of fuel cost with valve point effect
- Minimization of voltage deviation
- Enhancement of voltage stability (L-max)

-Minimization of emission

- Minimization of active power loss

2.1.1 *Control variables*

The vector of power network control variables is expressed as follows:

$$u=\left[P_{G_2}\cdots P_{G_{NG}},V_{G_1}\cdots V_{G_{NG}},Q_{C_1}\cdots Q_{C_{NC}},T_1\cdots T_{NT}\right] \tag{2.3}$$

Where, P_{G_i} is the i-th active power bus generator. Chosen from generators bus 1 as swing bus is represented just and any one of the generator buses can be swing bus. V_{G_i} is the voltage magnitude at i-th voltage controlled generator bus, T_j is the j-th branch transformer tap, Q_{C_k} is the shunt compensation at k-th bus. N_G , N_C and N_T are the generators' number, transformers and shunt VAR compensators. Any value within its range can be assumed as a control variable. Practically, transformer taps are not constant. Be that as it may, the tap settings indicated are in p.u. and outright voltage's estimation is not represented. Subsequently, for the aim of this study and to compare with previously described results, all control variables including tap settings are viewed constant for general cases of study.

2.1.2 State variables

The power system's state variables can be expressed through vector x as:

$$x = \left[P_{G_1}, V_{L_1} .. V_{L_{NL}}, Q_{G_1} .. Q_{G_{NG}}, S_{l_1} .. S_{l_{nl}} \right] \tag{2.4}$$

where, P_{G_1} is the active power of generator at slack bus, Q_{G_i} is the generator's reactive power linked to bus i, is the p-th load bus's bus voltage (PQ bus) and q-th line's line loading of is specified by. NL and nl are the load buses' number and lines of transmission respectively[40].

2.1.3. Power System Constraints

As aforesaid earlier, the problem of OPF presents both operational constraints on equality and inequality. These constraints are defined as follows:

2.3.1.1 Equality constraints

In OPF, the reactive and real power equilibrium equations are represented the system constraints of equality formulated as for all system buses:

$$P_{G_i} - P_{D_i} - V_i \sum_{j=1}^{NB} V_j \left[G_{ij} \cos\left(\delta_{ij}\right) + B_{ij} \sin\left(\delta_{ij}\right) \right] = 0 \tag{2.5}$$

$$Q_{G_i} - Q_{D_i} - V_i \sum_{j=1}^{NB} V_j \left[G_{ij} \sin\left(\delta_{ij}\right) + B_{ij} \cos\left(\delta_{ij}\right) \right] = 0 \qquad (2.6)$$

Where, $\delta_{ij} = \delta_i - \delta_j$ will δ_i and δ_j is the voltage angles among bus i and bus j, NB is the buses' number, Q_{Di} and P_{Di} are reactive and real load demands. G_{ij} is the transfer conductance and B_{ij} is the susceptance among bus i and bus j, respectively.

2.3.1.2 Inequality constraints

The inequality's constraint in the OPF reflects the equipment's operating limit in the power system, and too reflects the limitation of the line and the load bus to ensure the safety of the system.

a) Generator constraints:

$$V_{G_i}^{\min} \le V_{G_i} \le V_{G_i}^{\max} \qquad \forall i \in NG \qquad (2.7)$$

$$P_{G_i}^{\min} \le P_{G_i} \le P_{G_i}^{\max} \qquad \forall i \in NG \qquad (2.8)$$

$$Q_{G_i}^{\min} \le Q_{G_i} \le Q_{G_i}^{\max} \qquad \forall i \in NG \qquad (2.9)$$

b) Transformer constraints:

$$T_j^{\min} \le T_j \le T_j^{\max} \qquad \forall j \in NT \qquad (2.10)$$

c) Shunt compensator constraints:

$$Q_{C_k}^{\min} \le Q_{C_k} \le Q_{C_k}^{\max} \qquad \forall k \in NC \qquad (2.11)$$

d) Security constraints:

$$V_{L_p}^{\min} \le V_{L_p} \le V_{L_p}^{\max} \qquad \forall p \in NL \qquad (2.12)$$

$$S_{l_q} \le S_{l_q}^{\max} \qquad \forall q \in nl \qquad (2.13)$$

The control variables in constraints of inequality are self-limiting. The technique of optimization chooses a viable value for every like variable within the determined scope. Efficient methods for dealing with constraints of inequality related to dependent or state variables are used.

2.2 Economic load dispatch

The Economic Load Dispatch (ELD) can be described as the process of allocating generation level to generating units, thus that the load of the system is provided fully and most economical way. For interconnected systems, it is needed to decrease the costs. Economic load dispatch is employed to determine the level of production in every plant, so the total cost of power generation and transmission is least for the specified schedule of load. The main goal of economic load dispatch is to reduce the total cost of generation. The technique of economic load dispatch for the generating units at different loads should have the total fuel cost at least [3].

In a typical power system, several generators are carry out to supply sufficient total product to meet a given total consumer demand. Every of these generating stations can and generally does have a unique hourly cost characteristic of its product operating area. A station has additional operating costs for fuel and maintenance; and fixed costs related with the plant itself which may be quite large in the case of a nuclear power plant things get more complicated, for example, when utilities try to consider transmission line losses and seasonal changes related with hydroelectric power plants.

There are many traditional techniques used to solve economic load dispatch problems, like Newton-Raphson method, Lagrange multiplier methods and lambda iteration method. In the traditional methods, it is difficult to solve the best economic problems if the load changes. It needs to calculate the economic load dispatch that is used for a long time each time in each compute cycle. This is a calculation process in which the desired total generation is distributed between the generated units in operation, by decrease the chosen cost criteria and making them subject to loading and operation constraints.

2.2.1 Generation scheduling’s requirement

In the actual power system, the distance between the power plant and the load center is different, and the fuel cost is various. In addition, in normal operation, the generation capacity exceeds the total load demand and the losses. Therefore, there are several options for scheduling generation. In interconnected power system, the goal is to get the active and reactive power scheduling of every power plant in this way in order to minimize operating costs. This means that the active and reactive power of the generator is admit to change within a certain limit in order to meet specific load demand at minimal fuel cost. This is known as the "Economic Load Dispatch" problem (ELD). The main challenge for whole power utilities is not only to meet consumer demand for electricity, but also to reduce costs. Any power system can consist of multiple generating units with generators' number, and the cost of running these generators is generally not proportional to their output. Thus, the challenge of power utilities is to try to equilibrium the total load between generators as effectively as feasible.

The economic load dispatch problem (ELD) presumes that the amount of power to be provided by a given set of units of constant units for an offered time interval and effort to reduce the cost of supplying this energy under to the constraints of the generating units. As a result, this is related to minimize the total cost over the full dispatch period. Thus, the major purpose of the economic load dispatch problem is to decrease the total cost of generating active power (production) at different stations while meeting the loads and losses in the transmission links [4].

2.2.2 Formulation of economic load dispatch

The easy problem of economic load dispatch is to ignore the transmission line losses.

Because of this, the total demand PD is the sum of whole generations.

A cost function $F_i\left(P_{gi}\right)$ is presumed to be known for every plant.

The problem is to get the active power generation, P_{gi} for every plant, the total cost of operation $F\left(P_{gi}\right)$ is the minimum and the generation remains between the minimum generation ($P_{gi}^{\min}$) and maximum generation ($P_{gi}^{\max}$).

Assuming that there is a station with a *NG* generators and a given real power load demand PD, the active power generation P_{gi} of every generator should be allocated in order to minimize the total cost. Therefore, the optimization problem can be formulated as:

Minimize:

$$F_i\left(P_{gi}\right)=\sum_{i=1}^{NG} F\left(P_{gi}\right) \tag{2.14}$$

Subject to:

(i) The energy balance equation

$$\sum_{i=1}^{NG} P_{gi} = P_D \tag{2.15}$$

The inequality constraints

$$P_{gi}^{\min} \le P_{gi} \le P_{gi}^{\max} \tag{2.16}$$

where

P_{gi} is the decision variable, i.e. active power generation is the P_D active power demand,

NG is the generation's number plants,

$P_{gi}^{\min}$ is the inferior permissible boundary of active power generation,

$P_{gi}^{\max}$ is the superior permissible boundary of active power generation,

$F_i\left(P_{gi}\right)$ is the operating fuel cost of the i^{th} plant and is given quadratic by the equation:

$$F_i\left(P_{gi}\right) = a_i + b_i P_{gi} + c_i P_{gi}^2 \tag{2.17}$$

Where a_i, b_i and c_i are the cost coefficient of the generator unit. The mentioned constrained problem of optimization is transformed to unconstrained optimization problem. Use language multipliers, where function is reduced (or maximized) and have aspect conditions in the form constraints equality. Employ this technique an augmented function is outlined as [4]:

$$L\left(P_{gi}, \lambda\right) = F\left(P_{gi}\right) + \lambda\left(P_D - \sum_{i=1}^{NG} P_{gi}\right) \tag{2.18}$$

Where λ is the Lagrange multiplier

A needful condition of a function $F\left(P_{gi}\right)$, which has a relative minimum value by the energy balance constraint at the point P_{gi}, and is a partial derivative of the Lagrange function outlined by $L = L\left(P_{gi}, \lambda\right)$ relative to each of its parameters should be zero. Therefore, the needful conditions for the problem of optimization is:

$$\frac{\partial L\left(P_{gi},\lambda\right)}{\partial P_{gi}}=\frac{\partial F\left(P_{gi}\right)}{\partial P_{gi}}-\lambda=0 \tag{2.19}$$

and

$$\frac{\partial L\left(P_{gi},\lambda\right)}{\partial \lambda}=P_D-\sum_{i=1}^{NG}P_g=0 \tag{2.20}$$

where

$\frac{\partial F\left(P_{gi}\right)}{\partial P_{gi}}$ Is the incremental fuel cost of the i^{th} generator.

The generator's optimal load corresponds to an equal incremental cost point of whole generators.

Eq. (2.18), named the coordination equations numbering *NG* are solved simultaneously with the load demand to obtain solution of Lagrangian multiplier λ and the optimal generation of NG generators. Taking into account the cost function offered by Eq. (2.17), incremental costs can be outlined as

$$\frac{\partial F\left(P_{gi}\right)}{\partial P_{gi}}=2a_iP_{gi}+b_i \tag{2.21}$$

Substituting the incremental cost into equation (2.18), in this equation becomes

$$2a_iP_{gi}+b_i=\lambda \text{ (i=1 ,2,……,NG)} \tag{2.22}$$

Rearranging Eq. (2.22) to get P_{gi}

$$P_{gi}=\frac{\lambda-b_i}{2a_i}\text{(1 ,2,….,NG)} \tag{2.23}$$

Substituting the value of P_{gi} in Eq. (2.20), we get:

$$\sum_{i=1}^{NG}\frac{\lambda-b_i}{2a_i}=P_D \tag{2.24}$$

Or

$$\lambda=\frac{P_D+\frac{\lambda-b_i}{2a_i}}{\sum_{i=1}^{NG}\frac{\lambda-1}{2a_i}} \tag{2.25}$$

2.2.3 Economic load dispatch with quadratic cost function

The total cost of operating the generators involves fuel and keeping costs, but for simplicity's sake, only the variable costs to be taken into account are fuel costs. Fuel costs are significant for thermal power plants. The cost function is treated as a quadratic curve.

$$F=\sum_{i=1}^{NG} f_i(P_{gi})=\sum_{i=1}^{NG} a_i+b_i P_{gi}+c_i P_{gi}^2 \tag{2.26}$$

The NG is the total generation's number units, P_{gi} is the active power generation of ith unit. i = 1,2 ..., to NG subject to the gratification the power flow equations[5].

2.2.4. Economic load dispatch with valve point loading

Valve-point impact should be considered for more realistic and exact modeling of fuel cost function. The generating units with multi-valve steam turbines display a more prominent variety in the fuel-cost functions [6]. The valve loading impact of multi-valve steam turbines is modelled as sinusoidal function, the absolute value of which is added to the basic cost function. The real cost curve function of the steam plant becomes non-continuous as in Fig. 2. The aim of reducing generating fuel cost with valve-point effect is given by [7]

Thus, in fact, the ED problem's objective function has non-differential properties.

Therefore, the objective function must be consisting of a set of non-smoothing cost functions. taking into account the non-smoothing cost function of a generator units with a valve point effect, the objective function is usually explained as the superposition of the sinusoidal function and the quadratic function [8]:

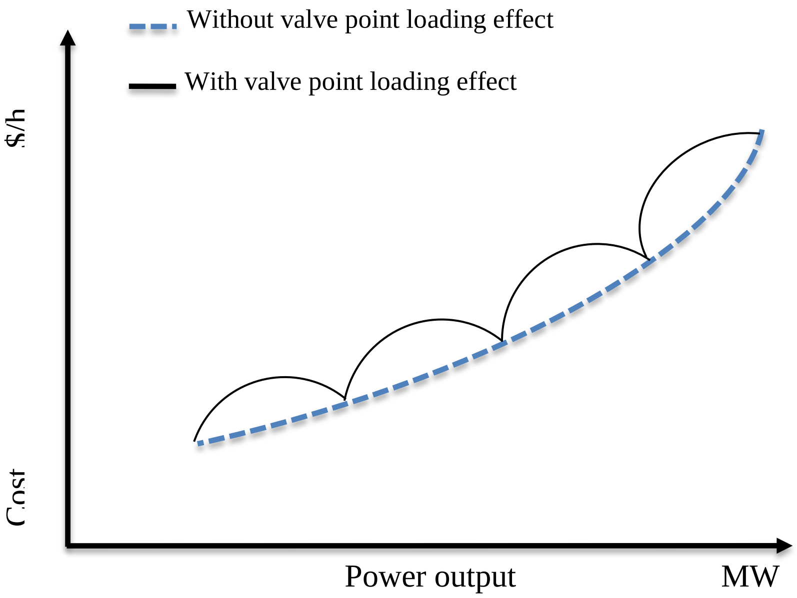

Figure 2.1 Cost function with valve-point effects [5].

$$F_i = a_i + b_i P_{Gi} + c_i P_{Gi}^2 + \left| d_i \times \sin\left(e_i \times \left(P_{Gi}^{\min} - P_{Gi} \right) \right) \right| \tag{2.27}$$

Where, d_i and e_i are the coefficients that show the valve-point loading effect.

As appear in Figure 2.1, this augments the nonlinearity of the curve as well as the local optima's number in the solution space [9] relative to the smooth cost function because of the valve point effects.

2.2.5. Economic emission/environment dispatch with valve point loading

The different objectives of the power systems are the generation cost, the transmission losses of the systems, environmental pollution, security, etc. These objectives are inherently conflicting and cannot be addressed through traditional single-objective optimization methods. EED is one of the major functions of current Energy Management System (EMS), which defines the best active power settings for generator units with two competitive objective functions, fuel cost and environmental pollution, while satisfying many equality and inequality constraints. Commonly, the mathematical model EED can be reported as next.

2.2.6. Emission Dispatch

Because of growing concern for environmental deliberations, society needs adequate and safe electricity, that is, not only at the cheapest reasonable price, but also at the lowest level of pollution [10].

The purpose of the ED problem is to reduce the total emissions of whole thermal units.

The emission of a fossil-based thermal generator unit respects on the amount of power generated by the unit.

Atmospheric pollutants caused by fossil fuel generators, like sulphur oxides (SO_X) and nitrogen oxides (NO_X), can be modeled separately or as the overall emission of the sum of a quadratic and exponential functions, and can be formulated as:

$$Min\left[Emi\right]=Min\left[\sum_{i=1}^{NG}E\left(P_i\right)\right]=Min\left[\sum_{i=1}^{NG}\left[\left(\alpha_i+\beta_i P_{G_i}+\gamma_i P_{G_i}^2\right)\times 0.01+\omega_i e^{\left(\mu_i P_{G_i}\right)}\right]\right] \quad (2.28)$$

Where $E\left(P_i\right)$ is the total emission issue in kg/h, α_i , β_i , γ_i ω_i and μ_i are the emission function coefficients of the ith generating unit.

2.2.7 Economic Emission Dispatch

The problem of power dispatch is formulated as a two-objective optimization problem as next:

$$\cos t=Min\left[\sum_{i=1}^{NG}F\left(P_i\right),Emi\right]=Min\left[\sum_{i=1}^{NG}\left(F\left(P_i\right)+Pf_i*Emi\right)\right] \quad (2.29)$$

EED is a problem of multi-objective, it is an incorporation of economic and environmental dispatches, that individually make up various single problems. At this point, this problem of multi-objective necessarily to be converted to a single objective form so as to achieve optimization. The transformation process can be done by employ the price penalty factor. Hence, a single-objective EED can be formulated as appear in Eq. (2.28)].

Among them, Pf_i is the price penalty factor. Pf_i is the ratio between the mean fuel cost and the mean emission of the plant's maximum power capacity [4].

2.3 Conclusion

The formulation of OPF problems, involving operational constraints, state variables and control variables of power system is deliberated in second chapter.

Chapter 2. Problem Formulation

This chapter is also devoted to a formulation of ELD to the operating costs and various aspects of the problem of economic dispatch, like with and without loss, with and without valve point loading effect and problem of economic emissions dispatch.

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Chapter 3: Hybrid Algorithm

3.1 Introduction

The resolution of optimization problems has become a central subject in operational research, the number of decision-support problems that can be formalized in the form of an optimization problem is in high growth [1].

Nowadays optimization has become an indispensable area for solving a number of problems in industry or other sectors [2]. Indeed, we have seen in recent years a very rapid growth of works using optimization methods. This trend can be seen in all areas of science.

In this chapter, we will discuss the general definitions of optimization methods that are divided under two deterministic and non-deterministic components. We also give a brief description of the problems dealt with throughout this manuscript.

3.2 Optimization problems

The formulation of optimization problems remains very ambiguous because of the variety of vocabulary and possible confusions that this could generate. We agreed to adopt the following vocabulary [3]:

-A single-objective optimization problem is defined by a set of variables, an objective function and a set of constraints.

-A multi-objective optimization problem is defined by a set of variables, a set of objective functions, and a set of constraints.

-The state space, also called the field of research, is all the areas of definition of the different variables of the problem.

-The variables of the problem known as variable design or decision can be of a diverse nature and expressing qualitative or quantitative data, in this thesis one is interested in the real case.

-The objective function or even (cost function) defines the goal to be achieved, we try to minimize or maximize this one.

-A multimodal function has several minima (local and global).

-While a one-mode function has only a minimum, the overall minimum.

-The set of constraints is generally a set of equality or inequality that the variables in the state space must meet. These constraints limit the search space.

-Optimization methods search for a point or set of points in the search space that satisfy all constraints, and that maximize or constrain the objective function.

3.2.1. Hybrid optimization methods

The use of hybrid methods allows combining the advantages of both types of methods (deterministic and non-deterministic), they can be seen as the perfect solution to the disadvantages and local methods and global methods. By the way, local methods lead to a local solution. While global methods consume a great deal of time, it seems clear that a trade-off between exploitation and exploration must be found hence the usefulness of hybrid methods. When hybridization is based on a true mastery of the idea behind each of the candidate methods, the increase in accuracy as well as the decrease in calculation time is ensured.

Two strategies can be used to explain strategy:

Strategy 1-for example, we can approach the global optimum by a random method and then refine the result by successively applying a local method. This hybridization is called beast hybridization because it applies one method after the other [4]. It is clear that the result will be better but at the expense of computational time, more time would be consumed than if the two methods had been applied separately. The real sense of hybridization, in this case, can be to apply a universal method and find the right moment to switch using a local method.

Strategy 2-We can also try to find a state of minimum local and stay there only if it is the best of local minimums (global).

3.2.1.1. Types of hybrid optimization methods

Assume a group of people necessity to carry object over long distances. In a series of hybrid strategies, one person will carry an object for a period of time, and then others will bear the load and carry it further [5]. This "tag group" technique continues until the needed distance is covered. These series methods could work well if the object is light and small. However, if the object is heavy or awkward in shape, then it will be hard for a person to wear it even for a short distance, if he can move it at whole.

In this case, it is obviously more efficient for two or more people to carry objects with each other in parallel technique. Through working with each other in a well-coordinated effort, the load can be shared so that each participant can contribute to the task. Every contribution, though small, decrease the load on the other members of the group, allowing the group to carry it quicker and farther with less stress.

A. Series hybrid optimization

In terms of optimization, a serial hybrid technique is developed by starting with one search technique, and then moving to another one (employ a various strategy than the first technique) to continue the study. There is no boundary to the number of various search strategies that can be employing in this sequential manner. Usually, a serial hybrid technique begins with a powerful search technique in global exploration, like a genetic algorithm, and ends with a local refinement strategy, like a gradient-based algorithm. Different other search techniques can be sandwiched between these two techniques. On some problems, this kind of series optimization technique has been appear to perform reasonably well compared to monolithic (single-strategy) techniques , when an suitable set of techniques and tuning parameters has been chosen [5].

The performance of a serial hybrid optimization strategy based on the specific techniques and tuning parameters is employed at every stage of the search. In order to every technique works alone, the progress is made at any time based on the effectiveness of the technique chosen for this problem and the efficiency of the information given by the previous search techniques.

As aforesaid in other publications, it is commonly unfeasible to know which techniques or adjustment parameter values will work well with a problem before it is solved. Thus, serial hybrid technique has the same fatal fault as most monolithic strategies, excluding that the number of unknowns is now multiplied by the number of various strategies employed.

Furthermore, additional unknowns are introduced, like the array of the strategies and the opportune time to stop one strategy in favor of another. Default values for these parameters may or may not apply to our present problem.

B. Parallel hybrid optimization

Parallel hybrid techniques; beat several of the disadvantages of serial hybrid techniques. In this strategy, various optimization techniques work simultaneously to solve a problem in a collaborative manner. Instead than contributing sequentially, these techniques work together to search for a design space and determination optimized solutions, such as several hands assist to carry a heavy load.

As with any perfect group, parallel hybrid techniques necessitate perfect leadership, coordination, communication and accountability. These attributes are structure into the technique's infrastructure at the beginning.

Instead of exploring and refining the various steps of a search separately, A parallel hybrid technique allows these two main activities to take place simultaneously and in synergistically. This not only velocities the search, but as well makes it more possible to find the global optimum.

In a series hybrid technique, the search history can be employed to define the individual technique(s) that has made the most important contribution to the search. However this is not feasible with a parallel hybrid technique, because every technique conducts very differently within a group than an individual.

Though, there are ways to hold an individual search strategy for responsible for its contributions in a parallel hybrid technique, and techniques that do not contribute sufficient over time can be replaced by new techniques or see their resources transferred to present techniques that contribute to a higher level.

The properties of a well-designed parallel hybrid optimization technique include shared find, intellectual diversity, synergistic search, and increased strength**,** and better strategies, quicker [5].

3.2.2. Choosing an optimization method

One wonders what is the purpose of classifying the types of problems and methods. In our opinion when a user is faced with a global optimization problem, the first thing to do is to understand the problem, namely:

-Assumptions about F (differentiation, convexity...),

-Assumptions about the field of research,

-Existence or not of constraints, what types of constraints,

-Cost of evaluating the function (CPU time, number of subprogrammes required),

-Ease of evaluation (access, explicit formula of F),

-Precision available on the calculations,

-Type of equipment used,

-Time available to solve the problem.

Thus, it is clear, that knowing a classification of problems and methods can facilitate the task of the user and guide him in his choice; which allows it to set its objectives accordingly. Because it is better to have an approximate solution (with insufficient accuracy) within a reasonable time than an exact solution (with the desired precision) out of time in certain contractual cases.

Unfortunately, no optimization method is capable of deal effectively with all cases. Indeed, [6] have shown that if we consider all of the possible optimization problems, then no algorithm is better than another ("No free lunch theorems for optimization").The choice of an algorithm can therefore not be made by comparison on general test cases, but must also study the problems representative of the applications envisaged. Comparing algorithms, local or global optimization can only take place once the problem dealt with is clarified, in other words the objective function. According to [2], optimization is not only a mathematical theory but also a kind of algorithmic cuisine where it is mainly the experience that guides the user in the choice of the algorithm to implement. To choose the most appropriate method for a specific problem, the main features taken into account are:

The ability to avoid local minima. It is according to the complexity of the problem that one or the other of the methods can be chosen. For example, if the objective function is convex it is probably advisable to work with a local method that allows reaching the optimum quickly compared to the methods of global optimization. That said, if the objective function is multimodal it is probably not the to apply a local method and use it for global methods becomes necessary. Although there are still several methods available, in this manuscript we have been rather interested in hybrid methods, given their efficiency.

The robustness of an optimum. The robustness of an optimum is also a decisive concept for designers, and should not be neglected when choosing the optimization algorithm. The form to be optimized is modeled in a deterministic way; this form is therefore optimized by neglecting the uncertainties linked for example to the manufacturing processes or to the simplifications of the problem. To decrease the probability that the performances of the optimized form are not verified in reality, one must look for a robust optimum. A robust optimum is a solution that is not sensitive to uncertainties.

The ability to deal with mono-or multi-objective problems. Multi-objective optimization is a very active field of research because the economic and industrial stakes are enormous. Multi-objective optimization methods, allowing to provide the designer with a set of solutions corresponding to as many compromises between the different antagonistic objectives of the problem, hence their importance.

The speed of convergence. i.e. what is the number of variables to be evaluated to converge towards a global optimum? The answer to this question lies in the compromise that must be found between exploration and exploitation.

3.2.3 Exploration and exploitation of optimization algorithms

For an optimization algorithm, exploration is its ability to explore the field of variables to search for the best valley, i.e. the one that contains the global optimum. On the other hand, exploitation is its ability to converge quickly to the minimum of a given valley from a starting point. The success and effectiveness of a resolution technique is mostly dependent on a compromise between exploration and exploitation. Some methods, however, use only one of these operators to achieve the optimum. Thus, deterministic methods, exploiting derivatives the objective function and the constraints to reach quickly and precisely the local minimum closest to the starting point, favor the exploitation at the expense of the exploration.

Any optimization algorithm must use these two strategies to find the global optimum: Exploration for the search for unexplored areas of the research space and exploitation to exploit the acquired knowledge to the points already visited and thus find better points [8].

3.2.4 Continuous optimization with constraints

All of the methods described in the previous section apply to without constraints optimization problems. But in reality it is almost impossible to find this kind of problem, it is usual to put constraints on the design variables or even constraints imposed by the specifications. Therefore, the consideration of these constraints when solving an optimization problem must take place. In other words, some constraint optimization methods must be applied. The idea is to substitute the function to minimize another function including constraints. We then obtain the optimum by searching for the minima of a suite of functions without constraints.

3.2.5 Single-objective optimization problem [8]

Mathematically, in the case of minimization, a single-objective optimization problem is in the following form:

$$\textit{Minimizer } F(x) \begin{cases} h_i(x) = 0 \\ g_j(x) \le 0 \\ x_L \le x \le x_U \end{cases} \begin{matrix} i = 1, \ldots\ldots., m \\ j = 1, \ldots\ldots., k \end{matrix} \tag{3.1}$$

with $x \in IR$ is the vector of the decision variables, f the objective function, $h_1, \ldots, h_m$ and $g_1, \ldots, g_k$ are respectively the equality and inequality constraints and x_L, x_U are respectively the lower and upper bounds in the variable search domain.

3.2.6 Multi-objective optimization

Multi-objective optimization is a fundamental area of aid for the multi-criteria decision, which is necessary for the many scientific and industrial. Over the past two decades, a very large number of work, both theoretical and applied, have been published in this field. Solving a multi-objective optimization problem involves to determine the solution corresponding best to the preferences of the decision-maker among the solutions of good compromise. One of the most difficult questions is thus related to the identification of the optimal Pareto set, or an approximation of it for complex problems. In particular, many of the electrical problems encountered in the industry are multi-objective in nature [7].

This part is intended to introduce the prerequisites necessary for a good understanding of this thesis. So, as a first step, we will present the context of multi-objective optimization, the main definitions, and the key issues related to this area of research, especially with regard to the resolution approaches for which we will try to take a critical look at each of them.

3.2.7 Formulation of a multi-objective problem

A multi-objective or multi-criteria problem can be defined as a problem where we try to optimize several components of the objective function vectors, while satisfying a set of constraints. Unlike a single objective problem, the solution is not unique but consists of a set of solutions called Pareto optimal.

The mathematical formulation of a multi-objective optimization problem is given as follows:

$$Minimizer\ F(x) = \left(f_1(x), \ldots, f_l(x)\right) \begin{cases} h_i(x) = 0 \\ g_j(x) \le 0 \\ x_L \le x \le x_U \end{cases} \begin{matrix} i = 1, \ldots\ldots, m \\ j = 1, \ldots\ldots, k \end{matrix} \qquad (3.2)$$

With $x \in IR$ is the vector of decision variables, $\{f_1, \ldots, f_l\}$ is the set of objective functions.

The main difficulty of a multi-purpose problem is that there is no definition of the optimal solution. The decision maker can simply to express the fact that one solution is preferable to another, but there is not a better solution than any other. Therefore, to solve a multi-objective problem is not to look for the optimal solution but the set of satisfactory solutions for which we will not be able to perform a classification operation.

Multi-objective problem solving methods are therefore decision support methods because the final choice will be left to the decision maker.

To address this problem, the scientific community has adopted two types of behavior:

-Bring a multi-objective problem to a single objective problem using weights;

- Attempt to respond to the problem by taking into account the set of objective functions [8].

It is very difficult to recommend a 100% behavior in relation to the other. The difference between these two behaviors is expressed in the figure below. Either the decision-maker intervenes from the outset of the definition of the problem, expressing his preferences, in order to transform a multi-objective problem into a single-objective problem. Either the decision maker makes his choice in all the solutions proposed by the method multi-purpose optimization.

The main quality of a multi-purpose optimization method is make decisions easier and less subjective.

3.3. Proposed Hybrid method

Enhanced efficiency is often carried out by hybridizing the technique and deterministic optimization methods. Enhancing the searching capability of the optimal solutions is the goal of technique hybridization.

Firstly, as portrayed here, a successful hybrid Meta heuristic Cuckoo Search Krill Herd (CS-KHA) [9] technique in light of KHA and CS is initially suggested to accelerate convergence. In CS-KHA, we use an essential KHA to select an encouraging solution set. Consequently, krill updating (KU) and krill abandoning (KA) operator started from CS algorithm are added to the method. The KU operator is to a decent encouraging arrangement; while KA operator is made use of further improving the investigation of the CS-KHA to substitute the worse krill's a small amount at the finale of every generation.

The performance of this approach is utilized to keep away from local optimum and obtain a worldwide ideal solution, in addition, minimal computational time to achieve the ideal solution, local minimum evasion, and quicker convergence, which produce them suitable for viable implementations for solving various constrained optimization problems. The purpose of this work is to develop an improved KHA called CS-KHA to solve OPF problem. So as to proven the evolution of the CS-KHA, its efficiencies are compared to CS, KHA and other well-known optimization methods.

3.3.1. Cuckoo search technique (CS)

Cuckoo's search technique is one of the latest incorporation to the nature inspirer’s group optimization heuristics. It has been offered by Young & Deb [10,11] and was demonstrate to be a favorable tool to solve difficult optimization problems.

Cuckoo birds pull attention due to their single aggressive breed strategy. Cuckoos indulge in brood parasitism. It is a parasitism's kind in which a bird (brood parasite) lays and abandons its eggs in another species’ the nest. Some species like the Ani and Guira cuckoos lay their eggs in communal nests, although they can eliminate eggs of others to augment the possibility of hatching their own eggs. Some host birds do not conduct friendly manner against intruders and come into direct conflict with them. In like situation host bird will throw these foreign eggs away. In other situations, further friendly hosts will easily abandon their nest and structure a novel nest elsewhere.

In Cuckoo Search technique, possibility solutions agree to cuckoo eggs. Natural systems are convoluted and therefore cannot be modeled by computer technique in their essential form. Natural’s simplification systems are needful for an effective application in computer techniques. One technique is to adapt the cuckoo search method through three below given approximation rules:

-Cuckoos select a random position (nest) to laying their eggs. Artificial cuckoo can only lay one egg at the time.

-The chosen process of the elitist is utilized, thus that only the highest quality eggs are passed to the following generation.

-Host nests number is not modified. Host bird detects a cuckoo egg with a possibility Pa ϵ [0.1]. If the cuckoo is revealed by the host, it can be thrown or the host can abandon its own nest and entrust it to the cuckoo intruder.

Given the optimization problem, the quality (fitness) of a solution can easily be proportional to its objective function's value. An easy representation where an egg in a nest illustrates a solution and a cuckoo egg illustrates a new solution is employed here. The goal is to use the novel potentially better solutions (Cuckoos) to replace the most difficult solutions found in nests.

When generating novel solutions, x_i^{t+1} for *ith* Cuckoo, a Lévy flight is carried out employ the next equation.

$$x_i^{t+1} = x_i^t + Q \oplus Levy\left(\gamma\right) \tag{3.3}$$

Where Q > 0 is the step size parameter of step and must be selection taking into accounts the selection of the problem and set on the unit in the CS [12]. It must be noted that in this novel version, the existing positions of the solution are applied instead of the superior solution as to the origin of Levy's flight. but in this case, random walking via the L'evy flight is more effective at exploring the search space because its step length is considerable longer in the long run. The L'evy flight basically expands a random walk while the random step length is taken from a distribution of the L'evy.

Some of the new solutions should be generated by L'evy walk around the preferable solution get so far, this will velocity up local research. Nevertheless , a substantial fraction of the new solutions should be generated by far area randomization and whose locations should be far enough from the current preferable solution, this will make certain the system will not be trapped in a local optimum.

Levy's flights as random walks: Levy's flights were notice between foraging of albatrosses patterns, fruit flies and spider monkeys. In wildlife, animals seeking for food in a random or quasi-random way. In common, the foraging path of an animal is actually a random walk because the next move is built on the existing position/state and the probability of transition to the next position. Which direction it selects depends implicitly on a possibility which can be modeled mathematically. For example, different studies have appear that the flight conduct of several animals and insects has proven the typical characteristics of Levy's flights.

Levy's flight is random walks in which the stage lengths are distributed agree to Levy's distribution function. Uninterrupted time random walks are random walks in which the stage lengths and wait times are distributed agree to Levy distributions. A current survey Reynolds & Frye (2007) display that fruit flies or Drosophila melanogaster search their landscape employ a series of straight flight punctuated by a sudden turn. Resulting to a levy's flight-style discontinuous scale-free search pattern. The Human's studies conduct of hunter-gatherer feeding patterns too show the Levy's flights' characteristic. Even light can be concerning to Levy's flights [13].

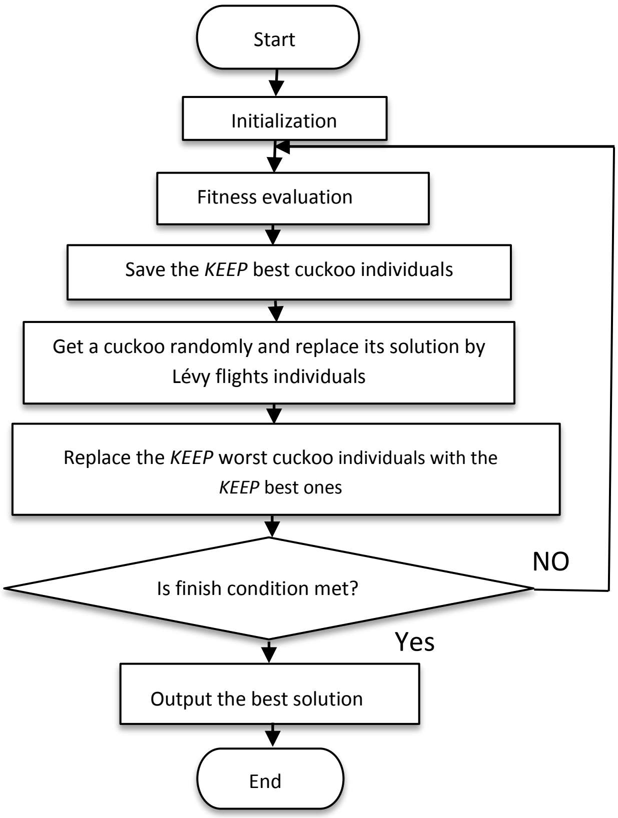

Figure.3.1. Flowchart of CS algorithm.

3.3.2. Krill herd algorithm (KHA)

Herding behavior of krill swarm, the formations of collections of different marine animals' species are under-scattered and non-random. Several studies have focused on capturing the underlying technicality governing the evolution of these formations [14,15]. The main technicality specified is related to the feeding capability, improved reproduction, and protection from predators, and environmental conditions [16]. Some mathematical models have been advanced to assess the relative contribution of these technicality build on experimental observations [14.15].

Antarctic krill is one of the preferable-studied marine animal's species. The krill herds are aggregations without parallel orientation present on time scales ranging from a few hours to days and spatial scales from 10 to 100 s of meters. One of the major characteristics of this species is its capability to form great swarms [17,18].

Over the past three decades, many studies have been behaved to understand the ecology and krill's distribution. Although there are still significant uncertainties regarding the forces determining the distribution of the krill herd [19], Conceptual models have been suggested to demonstrate the observed krill herds' formation [20]. The outcomes yielded by these conceptual frameworks appear that the krill swarms constitute the fundamental organizational unit of this species. So as to better understand the krill swarms' formation, the proximate causes and the factors that are adaptive interests of aggregation formation (ultimate effects) must be distinguished [21].

When predators, like seals, seabirds or penguins, attack krill, they eliminate the individual krill. These outcomes in a decrease in the density of krill. The krill herd's formation after predation depends on several parameters. The krill's herding individuals is a multi-objective process comprising two major objectives: (1) rising the density of krill and (2) run to food. In the current study, this process is taken into account to suggest a novel meta-heuristic algorithm for solving global optimization problems. The attraction of krill depending on density (rising density) and finding food (areas of high food concentration) are employed as targets which ultimately leads to the krill herd around the global minima. In this process, an individual krill is heading for the preferable solution when it is seeking for the highest density and food. In other words, the nearer the distance to the rise density and food, the less the objective function. In general, some coefficients must be specified for employ multi-objective herding conduct for a single objective one. In this survey, the coefficients are specified on the fundamental of a specialized literature review of the experimental observations of krill conduct [16, 22, 23] and too after an experimental survey.

3.3.2.1. Lagrangian model of the krill herding

Predation eliminates individuals, decreases the average density of krill, and keeps the krill swarms away from the food position. This process is supposed to be the initialization phase in the KH technique. In the natural framework, the fitness of every individual is assumed to be an incorporation of the distance of the food and the krill swarm's highest density. Thus, the fitness condition (imaginary distances) is the objective function's value. The temporal location of an individual krill on a 2d surface is governed by the next three major actions [16]:

i. Movement induced by other krill individuals;
ii. Foraging activity; and
iii. Random diffusion

It is recognize that an optimization technique must be able to search for spaces of arbitrary size. Thus, the next Lagrangian model is generalized to an n-dimensional decision space:

$$\frac{dX_i}{dt} = N_i + F_i + D_i \tag{3.4}$$

Where N_i is the movement induced by other krill individuals; F_i is the foraging motion, and D_i is the ith krill individuals' physical diffusion.

A. Motion induced by other krill individuals

According to theoretical evidence, the krill individuals try to ensure a high density and to move because of their mutual effects [16]. The movement induced direction, α_i is estimated from the local density of the swarm (local effect), the density of the target swarm (target effect) and the density of the repellent swarm (repellent effect) [16]. For an individual of krill, this movement can be explained as follows:

$$N_i^{new} = N^{\max}\alpha_i + \omega_n N_i^{old} \tag{3.5}$$

$$\alpha_i = \alpha_i^{local} + \alpha_i^{t\arg et} \tag{3.6}$$

where $N^{\max}$ is the upper induced velocity, ω_n is the inertia weight of the motion induced in the field [0, 1], N_i^{old} is the end motion induced, α_i^{local} is the local effect provided by the neighbors and $\alpha_i^{t\arg et}$ is the target direction effect provided by the preferable krill individual. According to the measured upper velocity's values induced [16], $N^{\max}$ is taken 0.01 (ms^{-1}).

The neighbors' effect can be supposed as an attractive/repulsive trend among individuals for local search. In this survey, the neighbors effect in an individual in the movement of krill is specified as follows:

$$\alpha_i^{local} = \sum_{j=1}^{NN} \hat{K}_{i,j} \hat{X}_{i,j} \tag{3.7}$$

$$\hat{X}_{i,j} = \frac{X_j - X_i}{\left\| X_j - X_i \right\| + \varepsilon} \tag{3.8}$$

$$\hat{K}_{i,j} = \frac{K_i - K_j}{K^{worst} - K^{best}} \tag{3.9}$$

Where K^{best} and K^{worst} are the preferable and worst fitness condition values of the krill individuals so far; K_i illustrates the fitness or value of the objective function of the *ith* individual *ith* krill; K_j is the fitness of *jth* (*j* = 1.2,..., NN) neighbor; X illustrates the related locations; And NN is the neighbors' number . For avoid singularities, a small positive number, ε is added to the denominator.

The right sides of equations (3.7)-(3.9) include some unit vectors and standardized fitness condition values. The vectors appear directions induced by various neighbors and every value displays the effect of a neighbor. The vector of neighbor can be attractive or repellent since the standardized value can be positive or negative.

For select the neighbor, various strategies can be employed. For example, a neighborhood ratio can be simply defined to find the number of nearest krill individuals. To employ the actual conduct of krill individuals, a sensing distance (ds) must be determined around an individual of krill and the neighbors must be found.

The sensing distance for every individual of krill can be specified employs various heuristic techniques. Here it is specified by employ the next formula for every iteration:

$$d_{s,i} = \frac{1}{5N} \sum_{j=1}^{N} \left\| X_i - X_j \right\| \tag{3.10}$$

Where ds, i is the sensing distance for the *ith* krill individual and *N* is the krill individuals' number. The factor 5 in the denominator is gained empirically. Employ Eq. (3.10), if the distance of two individuals of krill is less than the sensing determined distance, they are neighbors.

The target vector known to every individual of krill is the weakest fitness of an individual krill. The individual krill's effect with the preferable fitness form on the individual krill is taken into consideration employ the equation (3.11). This level leads to global optima and is expressed as follows:

$$\alpha_i^{t\arg et} = C^{best}\hat{K}_{i,best}\hat{X}_{i,best} \tag{3.11}$$

Where, C^{best} is the krill individual's effective coefficient having the preferable fitness to the individual of *ith* krill. This coefficient is know because $\alpha_i^{t\arg et}$ leads the solution to the global optima and it must be more effective than other krill individuals like neighbors. Here, the value of C^{best} is know as follows:

$$C^{best} = 2\left(rand + \frac{I}{I_{\max}}\right) \tag{3.12}$$

Where rand is a random value among 0 and 1 and is used to improve exploration, I is the actual iteration number and $I_{\max}$ is the iterations’ maximum number.

B. Foraging motion

The food search movement is expressed in terms of two major effective parameters. The first is the location of the food and the second is the preceding experience of the location of the food. This movement can be formulated for the individual ith krill as bellow:

$$F_i = V_f\beta_i + \omega_f F_i^{old} \tag{3.13}$$

Where

$$\beta_i = \beta_i^{food} + \beta_i^{best} \tag{3.14}$$

Where V_f is the food search velocity, ω_f is the inertia weight of food search movement in the field [0, 1], F^{old} is the last food search movement, β_i^{food} is attractive food and β_i^{best} is the effect of the preferable fitness condition of the ith krill so far. According to the measured food search velocity's values [22], w_f is taken $0.02\left(ms\right)^{-1}$

The food effect is know according to its position. The food's center must be found at the beginning and then try to formulate food attraction. This cannot be specified but can be estimated. In this survey, the virtual food's center concentration is estimated build on the distribution of the fitness form of krill individuals, which is inspired by the "mass's centre, "The food's center for every iteration is expressed as follows:

$$X^{food} = \frac{\sum_{i=1}^{N} \frac{1}{K_i} X_i}{\sum_{i=1}^{N} \frac{1}{K_i}} \tag{3.15}$$

Thus, the food attraction for the *ith* krill individual can be specified as below:

$$\beta_i^{food} = C^{food} \hat{K}_{i,food} \hat{X}_{i,food} \tag{3.16}$$

Where C^{food} is the food coefficient. Given that the food's effect in krill farming decreases over time, the food coefficient is specified as follows:

$$C^{food} = 2\left(1 - \frac{I}{I_{\max}}\right) \tag{3.17}$$

The food attraction is know to eventually attract the krill swarms to the global optima. Build on this definition, krill individuals normally herd about the global optima after some iteration. This can be seen as an effective global optimization strategy that assistance to enhancing the overall value of the KH technique.

The effect of the preferable fitness condition of the krill individual is too treated employ the next equation:

$$\beta_i^{best} = \hat{K}_{i,ibest} \hat{X}_{i,ibest} \tag{3.18}$$

Where $\hat{K}_{i,ibest}$ is the preferable visited location previously of the individual ith krill.

C. Physical diffusion

The physical diffusion of krill individuals is seemed to be a random operation. This movement can be indicating in terms of maximum diffusion velocity and random directional vector. It can be expressed as below:

$$D_i = D^{\max} \delta \tag{3.19}$$

Where $D^{\max}$ is the maximum diffusion velocity, and δ is the random directional vector and its arrays are random values among -1 and 1. Macready and

Wolpert [23] suggested a field for maximum diffusion velocity of krill individuals as $D^{\max}$ = [0, 002, 0, 010] (ms^{-1}) and a random number in this field is too employed in this research. The better the krill location, the less random the movement is. Therefore, another term is added to the physical diffusion expressed to consider this effect. The movement's effects induced by other krill individuals and the food search movement reduce gradually with rising time (iterations). By indicate to Eq. (3.19), physical diffusion is a random vector and does not gradually decrease with augments in the iterations' number. So other term (Eq. (3.20)) is added to Eq. (3.19). This term linearly reduction the random velocity over time and operates on the essential of a geometric annealing program:

$$D_i = D^{\max}\left(1 - \frac{I}{I_{\max}}\right)\delta \qquad (3.20)$$

D. Motion Process of the KHA Algorithm

In general, the determined movements frequently change the location of a krill individual towards the preferable fitness. The food search movement and the movement induced by other krill individuals include two global strategies and two local strategies. These are employed in parallel which make KH a robust technique. According to the expressions of these movements for the individual ith krill, if the value of the fitness condition associated with every of the aforementioned efficacy factors (K_j; K^{best}; K^{food} or K_i^{best}) is better (inferior) than the fitness of ith krill, it has an attractive effect; furthermore it has a repellent effect. It is too apparent from the above expressions that a better fitness condition is more effective on the movement of the individual krill. The physical scattering implements a random search in the suggested technique. To employ various effective parameters of the movement during the time, the location vector of an individual of krill during the interval t to $t+\Delta t$ is presented by the next equation:

$$X_i\left(t+\Delta t\right) = X_i\left(t\right) + \Delta t\,\frac{dX_i}{dt} \qquad (3.21)$$

It must be noted that Δt is one of the most significant constants and must be carefully defined according to the optimization problem. This is in order to this parameter works as a scale factor of the velocity vector. Δt depends entirely on the search space and it appear that it can be gained simply employ the next formula:

$$\Delta t = C_t \sum_{j=1}^{NV} \left(UB_j - LB_j \right) \tag{3.22}$$

Where NV is the sum variables' number , and LB_j and UB_j are minimum and maximum limits of the variable ith (*j* = 1.2,..., *NV*), respectively. Thus, their subtraction's the absolute display the search space. It is empirically established that C_t is a constant number among [0, 2]. It is too clear that the low C_t values allow krill individuals to carefully search the space.

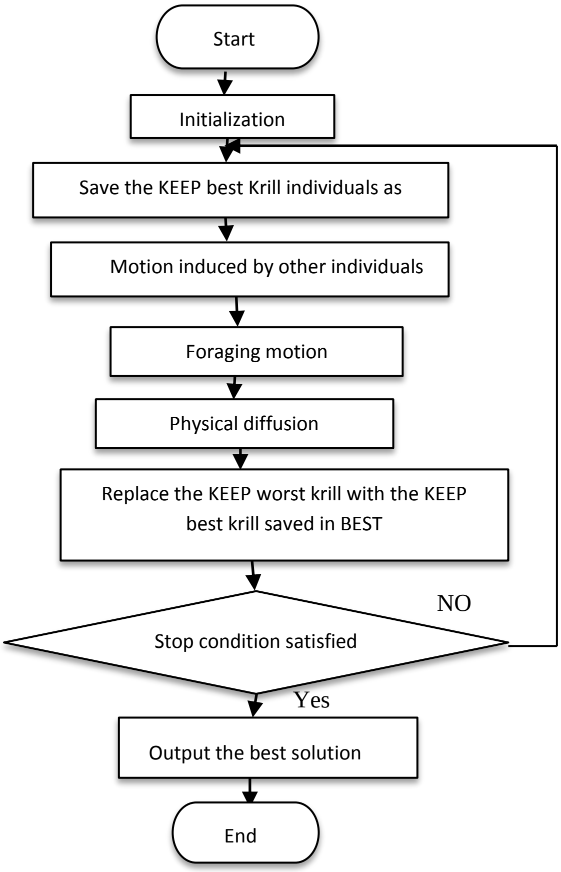

Figure.3.2. Flowchart of KHA algorithm.

3.3.3. Hybrid CS-KHA procedure

A. Hybrid Parallel CS-KHA

To enhance the search capacity of the fundamental KHA method, genetic techniques are added to the method [24]. Numerical results when compared with other methods show that KHA II (only added crossover operator) performed the best. Be that as it may, occasionally, KHA may have a likelihood of failing to discover better solutions to some difficult problems.

Consequently, in this work, a novel meta-heuristic algorithm by prompting KU operator and KA operator into KHA to form a new hybrid meta-heuristic method, so-called CS-KHA algorithm [25] is used to manage an OPF problem. The introduced KU/KA operators are roused by the authoritative CS algorithm. As such, in this work, the property of cuckoo used in CS is added to the krill to create a sort of super krill that can play out the KU/KA operator. The contrast amongst CS-KHA and KHA is that the KU operator as a local search tool is used to adjust the new solution for every krill rather than rand walks used as part of KHA (while in KHA II, genetic reproduction mechanisms are used). While KA operator is used to enhance further the exploration ability of the method by replacing some nests randomly thereby constructing new solutions. By the blending of CS and KH, CSKHA can investigate the new search space with standard KHA technique and KA operator and exploit the population information by KU operator. The main step of KU/KA operators used in CSKHA method is given in Algorithm 1 and Algorithm 2, respectively.

Algorithm 1 KU operator

```
Begin
    Get a krill i and update its solution using Lévy flights using equation (3.3).
    Evaluate its quality $F_i$
    Choose a krill $j$ randomly.
    If $\left(F_i \prec F_j\right)$
        Replace $j$ by the new solution and accept the new solution as $X_{i+1}$
    Else
        Update the krill position using equation (3.20) as $X_{i+1}$
    End if
End.
```

Algorithm 2 KA operator

```
Begin
    $K = rand\left(NP, D\right) \succ p_a$ .
    $P_1 = P; P_2 = P$
    For $i = 1$ to $NP$ (all krill ) do.
        $step = rand * (Y_i - Z_i);$
        $X_{new} = X_i + step \odot K\left(i,:\right);$
```

```
7.  End for
8.  For $i = 1$ to $NP$ (all krill ) do.
9.      If $F(X_{new}) \prec F(X_i)$ then
10.         $X_{new} = X_i; F(X_{new}) = F(X_i)$.
11.     End if
12. End for
13. End
```

Firstly in the CS-KHA method, standard KHA method uses three movements to look for the best solutions and engage these movements to lead the candidate solutions for the next generation. In this, KU operator is then used to carry out local search intensively to achieve better solutions. This operator can since it abuses the search space by Lévy flight.

Towards the end of each generation, the KA operator is used to additionally enhance the exploration of the CS-KHA by replacing a fraction (*pa*) of the worse krill. Along these lines, this component used in CS-KHA method can completely exert the strong exploration of the KH and get over the absence of weak exploitation of the KHA method. Additionally, it can fully extract the merits of KHA and CS. Above all, this technique can further unwind the conflict between exploration and exploitation effectively. Furthermore, another basic change is the presentation of elitism scheme into the CSKH.

Likewise, with other population-based methodologies, here, we use a more focused elitism technique to hold the best solutions in the population. This elitism system forbids the best krill from being demolished by three movements and KU/KA operator. By joining previously mentioned KU/KA operator and concentrated elitism strategy into unique KHA method to form a new CS-KHA algorithm (see Algorithm 3).

Algorithm 3 CS-KHA algorithm

```
1.  Begin
2.      Step 1: Initialization. Set the t =1,the population $P, V_f, D^{max}$, and $N^{max}$, $p_a$ and $KEEP$
3.      Step 2: Fitness evaluation.
4.      Step 3: While $t \prec$ MaxGeneration do.
5.              Sort the population.
6.      Store the KEEP best krill.
```

```
7.  for $i = 1 : N_P$ (all krill) do
8.  Perform the three motions.
9.      Update the krill position by KU operator (see Algorithm 1).
10.         Evaluate each krill by $X_{i+1}$.
11.  end for i
12.  Destroy the worse krill and build new ones by KA operator (see Algorithm 2).
13. Replace the KEEP worst krill with the KEEP best krill.
14. Sort the population.
15. $t = t + 1$.
16. Step 4: End while
17. End.
```

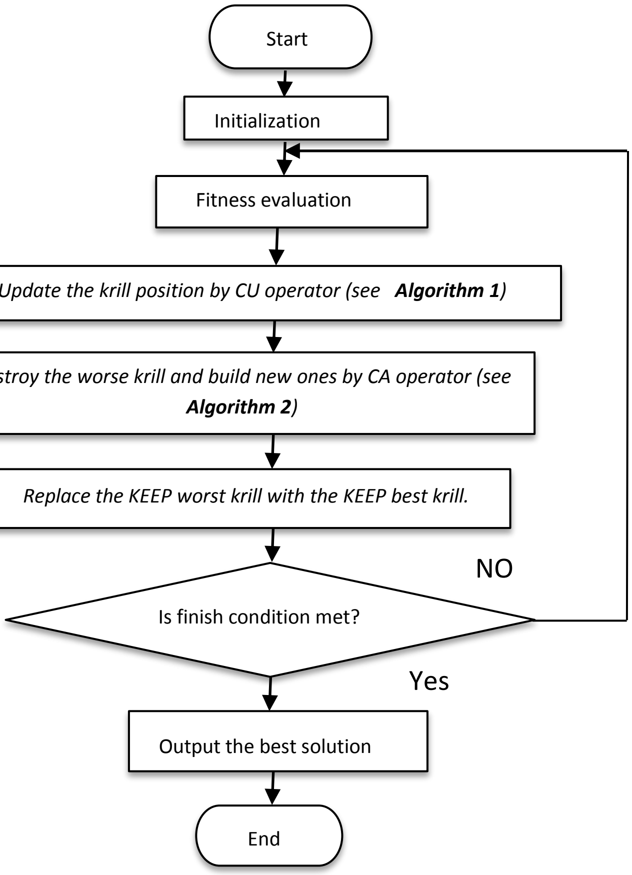

Figure.3.3.Flowchart of Hybrid parallel CS-KHA algorithm.

B. Hybrid Series CS-KHA

Based on the introduction of CS and KHA in earlier section, the detailed characterize of the suggested cuckoo search with Krill herd (KHA/CS) will be presented hybrid Series CSKHA in this section. As with else optimization techniques, an improved elitism scheme is combined into the CSKHA algorithm.

According to the above detailing, the krill herd /cuckoo search (KHA/CS) can be found in the corresponding flowchart appears in Figure 3.4.

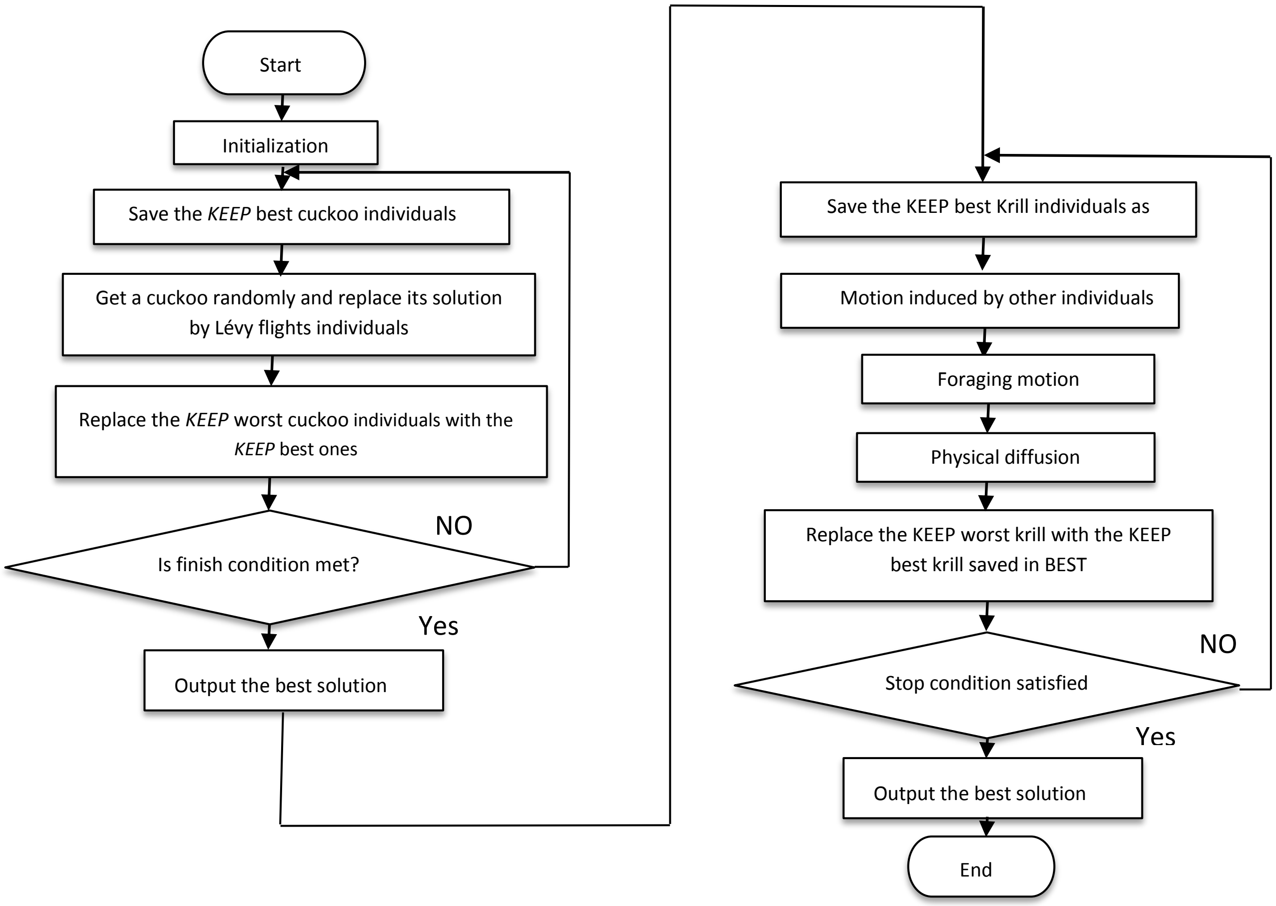

Figure.3.4. Flowchart of Hybrid Series CS-KHA algorithm.

3.4 Conclusion

In this chapter, we have presented a slide show on heuristic evolutional algorithms. Although the methods are very varied, the two Hybrid methods that we used are chosen for their speed and their resolution efficiency. For a this search, we make have hybrid the CS-KHA. The first time on the parallel and the second time on the series and the statement of which is the most successful to give a best solution ; which will subsequently minimize the calculation time and ameliorate the objective function.

Hybridization methods have been found to be the best solution for systems optimization.

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Chapter 4. Applications of hybrid techniques for OPF

4.1 Introduction

The main objective of OPF is to decrease the costs associated with the satisfaction of the load demand for a power system while maintaining the system's security. The costs related with power systems may respect on the situation, but usually they can be associated to the fuel cost (FC) of generating power in every generator. The system security's maintenance necessitates that each device in the power system be kept in a steady state within its desired operating range. This will involves the minimum and maximum products of the generators, the maximum MVA flows on the transmission lines and transformers, and the maintenance of the system bus voltage within a given range. The other objectives, like decrease network loss, enhancement of the voltage stability, improvement of the voltage profile and reduce emission can too be involved in the problem of OPF, as it has become increasingly simple to formulate and solve complex problems on a large scale problems with the advancement in computing technologies. It is to be important that the OPF addresses steady state operation of the power system.

The main objective is to develop a powerful methodology to solve the single and multi-objective problem of OPF. This chapter discusses the approaches proposed in the previous chapter, which has been extended to solve the OPF problem in order to effectively explore the solution space and prevent convergence to the local minimum.

4.2 Definition of Studied cases

19 cases are considered as shown in Table 4.1. These studied cases can be classified into the following categories:

- Single versus multi-objective category

  In this framework, mono-, bi- , triple, quad and 5 objective functions are considered.
- Economical/technical/ economical category:

  In this framework, the cases can be classified according the one or more of technical, economic and environmental benefits. The economic benefits aim to reduce the fuel generation costs, the technical benefits aim to minimize the power losses, improve the voltage profile and enhance the voltage stability.

Table 4.1. Summary of various OPF formulations

		Objective Function					
Test system	OPF formulation	Fuel costs (F1)	Fuel costs With Vpe	P losses (F2)	VD (F3)	Emissions (F4)	L-max (F5)
IEEE-30	Case 1	x					
	Case 2		x				
	Case 3			x			
	Case 4				x		
	Case 5						x
	Case 6	x			x		
	Case 7	x					x
	Case 8	x				x	
	Case 9	x		x			
	Case 10	x		x	x		
	Case 11	x		x		x	
	Case 12	x			x	x	
	Case 13	x		x	x	x	
	Case 14	x		x	x	x	x
IEEE-57	Case 15	x					
	Case 16				x		
	Case 17	x			x		
	Case 18	x					x
IEEE-118	Case 19	x					

X refers to a considered objective function

The CS-KHA algorithm has been used to solve the OPF problem for exam system and for many cases with various objective functions. The considered power systems networks are the IEEE 30-bus, IEEE 57-bus and IEEE 118-bus test system network. The advanced software program is written in MATLAB computing environment and used on a 2.20 GHz i7 personal computer. In our study, the CS-KHA population size or a numbers of stars is selection to be 50, 120, and 200.

4.3 IEEE 30-bus test system

In order to illustrate the performance of the proposed CS-KHA method, it has been examined first on the standard IEEE 30-bus test system. The standard IEEE 30-bus system selection in this work has the next characteristics [1]: 6-generators at buses 1, 2, 5, 8, 11 and 13, 4-transformers with off-nominal tap ratio at lines 11, 12, 15 and 36, 9- shunt VAR compensation buses at buses 10, 12, 15, 17, 20, 21, 23, 24 and 29.

In addition, line data, bus data, generator data, and lower and upper restriction for control variables are presented in [2].

For this exam system, Fourteen various cases have been studied with various objectives and all the obtained results are outlined in Tables 4.2, 4.4, 4.6, 4.8 and 4.10. The first column of this table appears the optimal control settings found here:

- P_{G_1} Through P_{G_6} and V_{G_1} through V_{G_6} represent the powers and the voltages of generator 1 through generator 6.
- T_{11} ,T_{12} , T_{15} *and* T_{36} are the tap settings of transformers involved between lines 11, 12, 15 and 36.
- $Q_{C_{10}}$, $Q_{C_{12}}$, $Q_{C_{15}}$, $Q_{C_{17}}$, $Q_{C_{20}}$, $Q_{C_{21}}$, $Q_{C_{23}}$, $Q_{C_{24}}$ *and* $Q_{C_{29}}$ represent the shunt VAR compensations connected to buses 10, 12, 15, 17, 20, 21, 23, 24 and 29.

Moreover, fuel cost *($/h)*, active power losses *(MW)*, voltage deviation and $L_{\max}$ represent the total fuel cost of the system, the total active transmission losses, the deviation of load voltages from 1 pu and the index of stability, respectively. More description of these results will be presented in the next sections.

Limits for the different variables for IEEE 30 bus, IEEE 57 bus and IEEE 118 bus test systems have been defined as follows:

$V_{G_i}^{\min} = 0.94$ pu , $V_{G_i}^{\max} = 1.1$pu , $T_j^{\min} = 0.9$ pu , $T_j^{\max} = 1.1$ pu , $V_{L_p}^{\min} = 0.9$ pu ,
$V_{L_p}^{\max} = 1.1$ pu

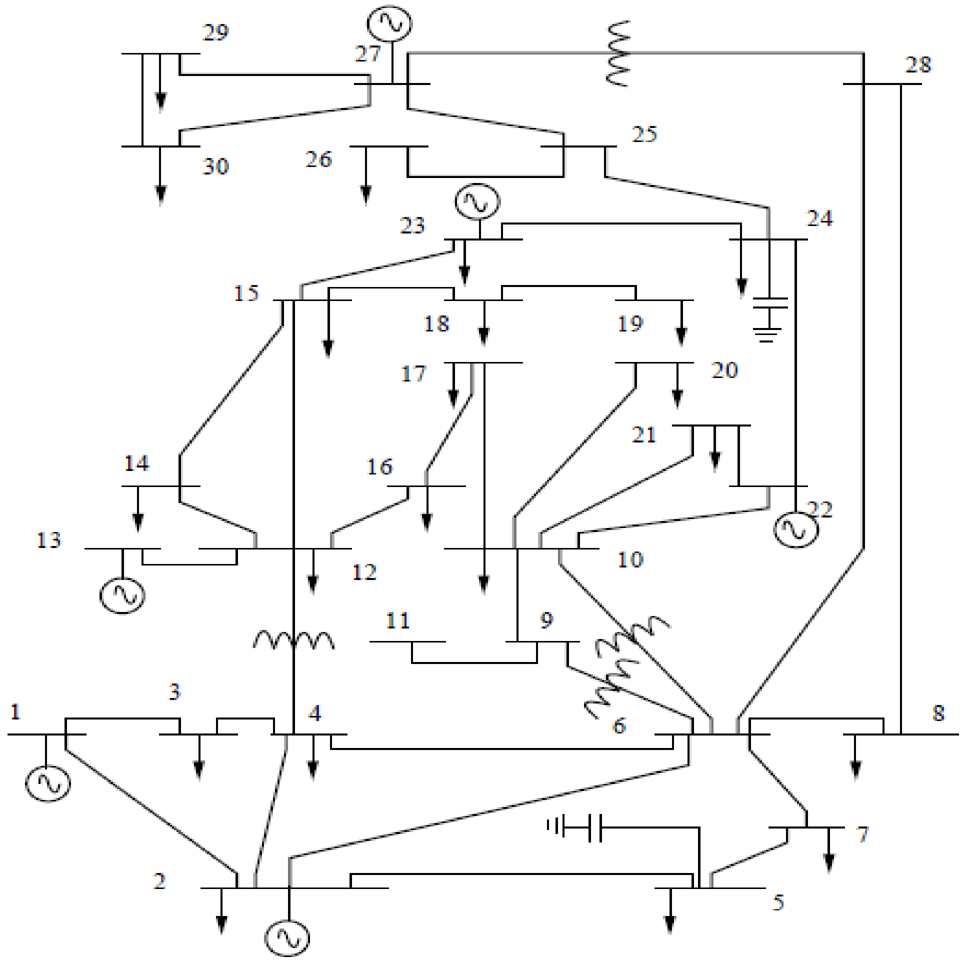

Figure.4.1. Single-line diagram of IEEE 30-bus system.

4.3.1 Case 1: Minimization of generation fuel cost

The first case studied in this work is the basic case of minimizing the cost generation fuel expressed by a quadratic function. Therefore, the objective function of this case is Eq. (4.1):

$$J = \sum_{i=1}^{NG} f_i \left(\$/h\right) \tag{4.1}$$

Where: *fi* - is the fuel cost of the *ith* generator. Usually, the OPF generation fuel cost curve is formulated by a quadratic function.

Hence, *fi* can be formulated as follows Eq. (4.2):

$$f_i = \left(a_i + b_i P_{G_i} + c_i P_{G_i}^2\right) \tag{4.2}$$

Where: a_i, b_i, c_i - are the element, the linear and the quadratic cost coefficients of the *ith* generator, respectively. The values of these coefficients are presented in [2].

Figure 4.2 appears the trend of total fuel cost over iterations. It seems that the proposed technique has good convergence characteristics. The optimal settings of control variables are presented in Table 4.2. The total fuel cost obtained by the suggested CS-KHA technique is (**799.0595**$/h). Compared to the original KHA, CS the total fuel cost is significantly decreased.

Using the identical conditions (limits of control variables, initial conditions, and system data), the results obtained in Case 1 apply the CS-KHA technique are compared to other methods described in the literature as appears in Table 4.3. There is some proof, that the suggested technique outperforms several methods used to solve the OPF problem by decreasing of generation fuel cost. For instance, the results obtained by the CS-KHA are better than the ones obtained by the KHA and CS methods.

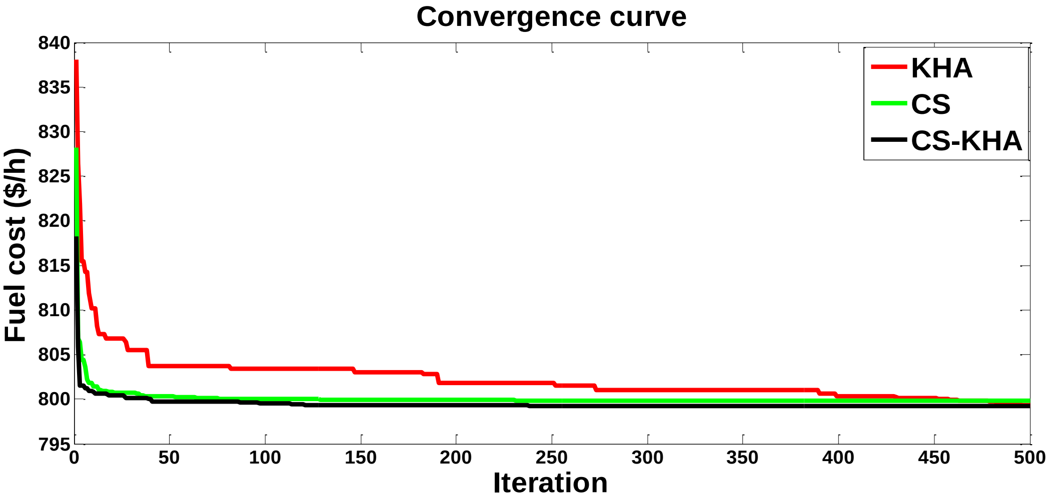

Figure 4.2. Convergence curves of Case 1

4.3.2 Case 2: Minimization of fuel cost considering valve point effect

So as to have a realistic and greater effective modeling of generator cost functions, the valve point–effect must be considered. The generating units with multi-valve steam turbines display a major variation in the fuel-cost functions and output a ripple-like effect [3]. So as to considered the valve-point effect of generating units, a model as a sinusoidal term is added to the cost function. Thus, the objective function can be formulated as follow:

Table 4.2. Optimal settings of the control variables for case1 to case 3.

Control variable	Case 1			Case 2			Case 3		
	CS-KHA	KHA	CS	CS-KHA	KHA	CS	CS-KHA	KHA	CS
P_{G1} (MW)	177.7695	176.6985	177.0700	199.9957	199.9873	200.0000	51.3818	51.4393	51.3414
P_{G2} (MW)	48.8746	48.4488	48.8674	43.0739	42.5401	43.8734	80	80	80

P_{G5} (MW)	21.0243	21.5532	21.3084	18.6343	19.1074	18.7891	49,9857	50	50
P_{G8} (MW)	21.5808	22.6989	21.0859	10.0300	10.0177	10.0000	34,9486	34,9753	35
P_{G11} (MW)	10.8258	10.4866	11.8626	10.0000	10.0960	10.0000	30	29,9825	30
P_{G13} (MW)	12.0000	12.1911	12.0000	12.0000	12.0241	12.0000	39,9359	40	40
V_1(p.u)	1.1000	1.1000	1.1000	1.1000	1.1000	1.1000	1,1	1,1	1,1
V_2(p.u)	1.0894	1.0891	1.1000	1.0854	1.0866	1.1000	1,09816	1,09784	1,1
V_5(p.u)	1.0634	1.0631	1.0728	1.0588	1.0583	1.1000	1,08195	1,07634	1,08197
V_8(p.u)	1.0696	1.0708	1.0796	1.0665	1.0657	1.0878	1,0879	1,08789	1,08923
V_{11}(p.u)	1.1000	1.1000	1.0957	1.1000	1.0985	1.1000	1,09744	1,07593	1,1
V_{13}(p.u)	1.1000	1.0944	1.1000	1.0975	1.0867	1.0160	1,1	1,1	1,1
Qc_{10}(Mvar)	0.9873	0.7887	0	1.2012	0.3180	5.0000	4,43281	2,63683	5
Qc_{12}(Mvar)	4.2959	0.8533	0	1.9153	0.1754	5.0000	0,0501051	2,52351	0
Qc_{15}(Mvar)	3.0959	0.0015	5.0000	0.1687	0.0254	0	3,00253	4,83028	5
Qc_{17}(Mvar)	5.0000	3.0633	5.0000	0.0310	0.0426	5.0000	5	0,614593	5
Qc_{20}(Mvar)	4.4733	3.4508	3.5533	5.0000	3.3646	5.0000	4,60232	2,72727	0
Qc_{21}(Mvar)	4.4607	0.4024	5.0000	0.1385	2.6324	5.0000	5	0,860869	5
Qc_{23}(Mvar)	0.3577	1.9594	5.0000	2.1640	0.8609	5.0000	4,66632	0,0001643	5
Qc_{24}(Mvar)	5.0000	2.3827	5.0000	5.0000	1.2249	5.0000	4,96554	0,607786	0
Qc_{29}(Mvar)	3.4597	2.5427	5.0000	0.0572	2.9633	5.0000	1,64923	2,20552	5
T_{6-9}	1.0315	1.0077	0.9718	1.0763	1.0090	1.1000	1,02266	1,07635	0,94417
T_{6-10}	0.9073	1.0210	1.1000	0.9027	1.0357	1.1000	0,946089	0,902381	1,1
T_{4-12}	0.9875	1.0364	1.1000	1.0359	1.0579	0.9000	0,985575	1,04252	1,0088
T_{28-27}	0.9785	0.9963	1.0194	0.9805	1.0057	1.1000	0,981985	0,998428	0,996249
Fuel cost ($/h)	**799.0595**	**799.4972**	**799.6547**	**830.0981**	**830.4199**	**833.5157**	966.7594	967.3441	967.2842
VD	1.7638	1.1245	1.3088	1.2223	0.8337	0.9003	1.9906	1.3679	1.7505
$L_{\max}$	0.1290	0.1357	0.1350	0.1342	0.1393	0.1487	0.1273	0.1333	0.1294
Emission (ton/h)	0.3685	0.3653	0.3662	0.4425	0.4423	0.4424	0.2073	0.2073	0.2072
$p_{loss}(MW)$	8.6750	8.6771	8.7944	10.3339	10.3726	11.2625	**2.8521**	**2.9471**	**2.9915**

Table 4.3. Comparison of the results obtained for Case 1to Case 3.

Case 1		Case 2		Case 3	
Algorithms	Fuel cost($/h)	Algorithms	Fuel cost ($/h)	Algorithms	Ploss (MW)
CS-KHA[1]	**799.0595**	CS-KHA[1]	**830.0981**	CS-KHA [1]	**2.8521**
KHA	**799.497**	KHA	**830.4199**	KHA	**2.9471**
CS	**799.6547**	CS	**833.5157**	CS	**2.9915**
CS-KHA[2]	**799.0723**	CS-KHA[2]	**830.1103**	CS-KHA [2]	**2.8527**
BHBO[4]	799.921	BSA [6]	830.7779	MSA[7]	3.1005
ARCBBO [5]	800.5159	ICBO [8]	830.4531	ABC[10]	3.1078
BSA[6]	799.0760	CBO[8]	830.473	ARCBBO[9]	3.1009
MSA[7]	800.5099	ECBO[8]	830. 587		
BBO[6]	799.1267	DE[6]	830.4425		

[1] refers to the hybridization method on the parallel, [2] refers to the hybridization method on the series.

$$f\ (x\,,u\,) = \sum_{i=1}^{NG} \left(a_i + b_i P_{G_i} + c_i P_{G_i}^2\right) + \left|d_i \times \sin\left(e_i \times \left(P_{G_i}^{\min} - P_{G_i}\right)\right)\right| \tag{4.3}$$

Where: d_i and e_i are the coefficients that show the valve-point loading effect.

In this case to arrive at a rise in cost than in case 1 with a conclusive value being **830.0981**$/h, obtained by CS-KHA. The optimal control variables obtained are shown in Table 4.2 output outcome of a method used in our study are better than most of the results revealed in past literature on the problem of OPF that is presented in table 4.3.

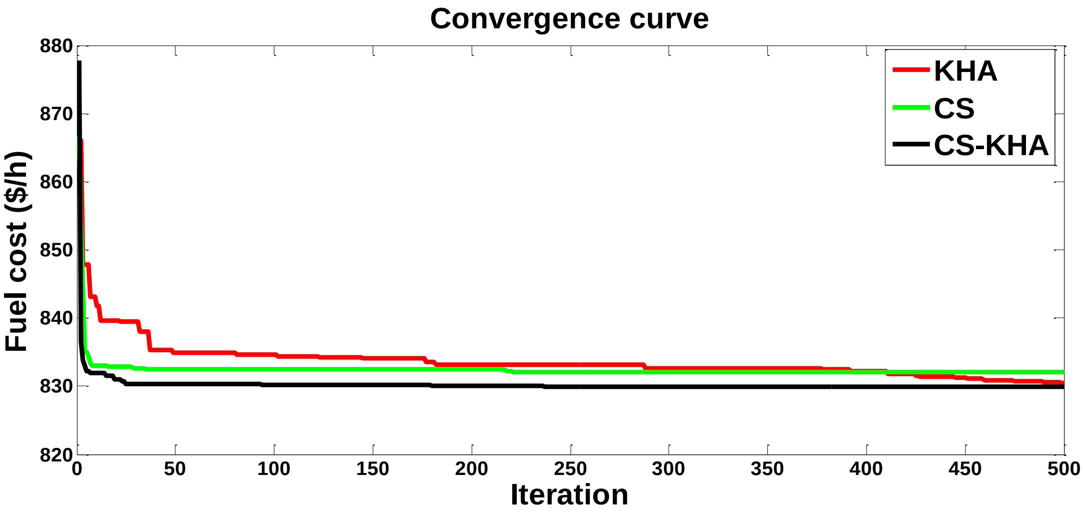

Figure 4.3. Convergence curves of Case 2

4.3.3 Case 3: Minimization of real power loss

In this case, the purpose of the OPF problem is to minimize power losses; the real power loss to be minimized is formulated as follows, Eq. (4.4):

$$f\left(x,u\right)=P_{loss}=\sum_{i=1}^{nl}\sum_{j=1,j\neq i}^{nl}G_{ij}\left[V_i^{\,2}+V_j^{\,2}-2V_iV_j\cos\left(\delta_{ij}\right)\right] \tag{4.4}$$

Where: $\delta_{ij}=\delta_i-\delta_j$ is the difference in voltage angles between bus i and bus j and G_{ij} is transfer conductance.

The tendency to decrease the objective function of total real power transmission loss using the CS-KHA technique appears in Figure 4.4. The optimal settings of the control variables are presented in Table 4.2 in this case 3 by CS-KHA result in real power losses of 2.8521 MW, better than all the results summarized in Table 4.3.

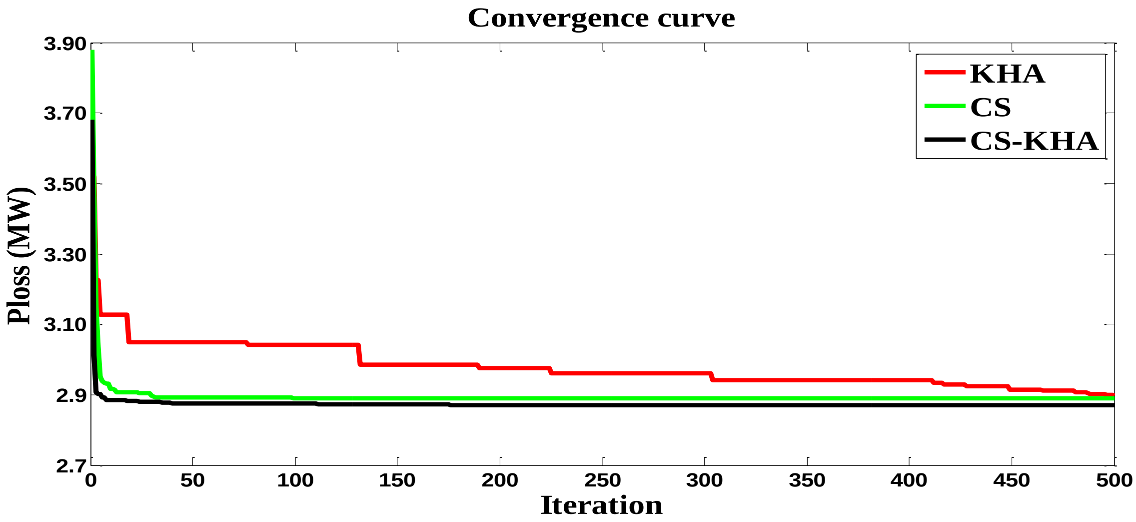

Figure 4.4. Convergence curves of case 3

4.3.4 Case 4: improved voltage profile

Bus voltage is one of the most significant and considerable security and service quality indices [2]. Reducing only the voltage profile in the OPF problem as in Case 1 may result in a suitable solution, but voltage profile may not be reasonable. Consequently, this case purposes at improve voltage profile by considering an objective function.

The voltage profile is optimized by reducing the load bus voltage deviation (VD) from 1.0 p.u, the objective function, in this case, can be formulated as follows Eq. (4.5):

$$J_{voltageDeviation} = \sum_{i=1}^{Nbus} |V_i - 1| \tag{4.5}$$

This case is only to improved voltage profile. The CS-KHA has been run for this case and the optimal control variables yielded are given in Table 4.4. It can appear from this table that the voltage profile has been improved compared with Case 4 because VD has been decreased to (0.0899 p.u). Hence, the generation cost has slightly increased to 922.6860 $/h.

4.3.5 Case 5: Enhancement voltage stability

The prediction of voltage instability is a problem of paramount significance in power systems. In [12], Kessel and Glavitch have developed a voltage stability index named $L_{\max}$ which is defined build on local indicators L_j and it is presented by Eq. (4.6):

$$L_{\max} = \max\left(L_j\right), \qquad j = 1, 2, ..., NL \tag{4.6}$$

Where: L_j is the local indicator of bus *j* and it is given as follows Eq. (4.7)

$$L_j = \left| 1 - \sum_{i=1}^{NG} H_{LG_{ji}} \frac{V_i}{V_j} \right| \qquad j = 1, 2, ..., NL \tag{4.7}$$

Where: *H* - matrix is produced by the partial inversion of Y_{bus}. More specifics can be given in [12]. The indicator $L_{\max}$ varies between 0 and 1 where the lower the indicator, the more the system stable. Thus, enhancing voltage stability can be obtained by the minimization of $L_{\max}$, the complete system given in [13].

The CS-KHA has been run for this case and the optimal control variables yielded are given in Table 4.4. It can appear from this table that the $L_{\max}$ has been enhanced compared with Case 4 because VD has been decreased to **0.1241**. Hence, the generation cost has slightly increased to **827.84454 $/h.**

4.3.6 Case 6: Minimization of fuel cost and voltage deviation

This case purposes at minimizing fuel cost with a improve voltage profile by considering a dual objective function.

The objective function, in this case, can be formulated as follows Eq. (4.8):

$$J = J_{\cos t} + wJ_{voltageDeviation} \tag{4.8}$$

$$J_{\cos t} = \sum_{i=1}^{NG} f_i \tag{4.9}$$

Where: *w* - is an appropriate weighting factor, to be chosen by the user to accord a weight to each of the two expressions of the objective function. In this case, *w* is selected as 100.

The CS-KHA technique has been utilized to search for the optimal solution of the problem. The variations in the fuel cost and voltage deviation through the iterations are outlined in Figure 4.5a and Figure 4.5b.

The optimal settings of the control variables are presented in Table 4.4. Apply CS-KHA the fuel cost and the voltage deviation yielded are (**803.6357**$/h) and (**0.1045** p.u.), respectively. The voltage profile obtained by CS-KHA is compared with other algorithms as appears in Table 4.5. It is clear that the voltage profile is the least among all other comparable methods. It is decreased from **1.7638** p.u. in the case 1 to **0.1045** p.u. in case 6. Hence, in case 6, the fuel cost is slightly augmented by 0.56% compared to case 1.

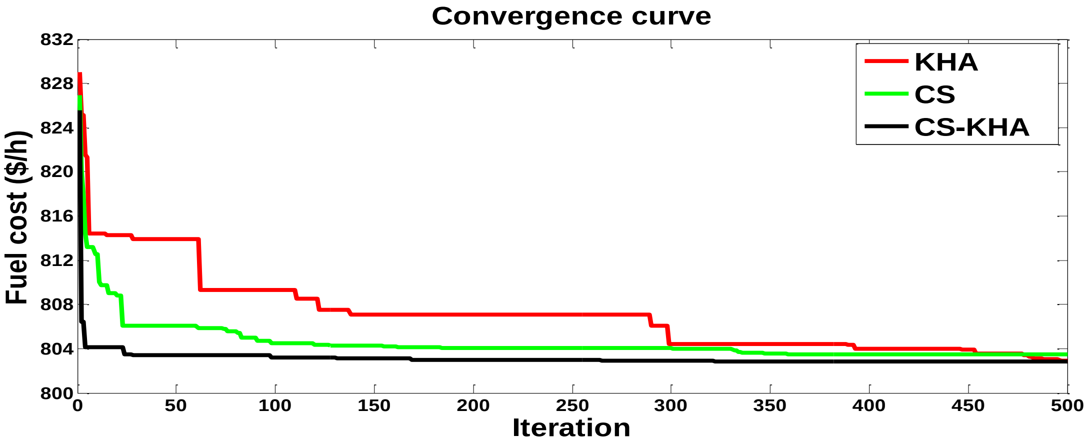

Figure 4.5a. Convergence curves of Case 6

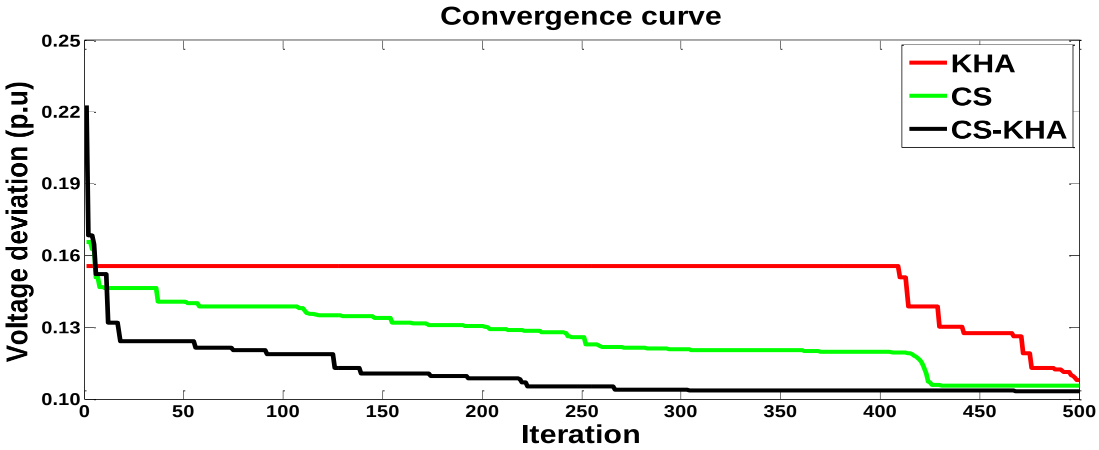

Figure 4.5b. Convergence curves of Case 6

4.3.7 Case 7: Minimization of fuel cost and enhancement of voltage stability

In this case study two objectives, fuel cost and voltage stability are whole reduced simultaneously. Hence, the objective function can be formulated as Eq. (4.10):

$$J(x,u)=\left(\sum_{i=1}^{NG} a_i + b_i P_{G_i} + c_i P_{G_i}^2\right)+\lambda_{L_{\max}}\left(L_{\max}\right) \quad (4.10)$$

Where: $\lambda_{L_{\max}}$ is a weighting factor chosen as 100 in this work. The results of the optimization study are presented in Table 4.6 while the direction of convergence appears in Figure 4.6a and 4.6b. It seems that the $L_{\max}$ has been decreased from

0.1290 to **0.1251**compared with CASE 1, Hence the results obtained are compared with other algorithms as given in Table 4.7.

Table 4.4. Optimal settings of the control variables for case 4 to case 6.

Control variable	Case 4			Case 5			Case 6		
	CS-KHA	KHA	CS	CS-KHA	KHA	CS	CS-KHA	KHA	CS
P_{G1} (MW)	90.9622	52.6637	63.0832	153.5067	130.4586	152.0606	176.2886	176.2432	177.5324
P_{G2} (MW)	79,863	79,9999	80	38,7744	72,6844	27,8169	49.1208	48.8217	49.1973
P_{G5} (MW)	50	50	50	29,2002	15	49,231	21.3698	21.6226	21.7154
P_{G8} (MW)	10	35	35	17,2576	10,3122	23,5847	22.0531	22.1836	22.8823
P_{G11} (MW)	30	30	30	16,9264	26,9247	12,3966	12.4129	12.3589	10
P_{G13} (MW)	28,6053	40	40	35,7696	35,3154	25,4327	12	12	12
V_1(p.u)	1,0035	1,00754	0,9906	1,0836	1,1	1,07954	1.0387	1.0462	1.0442
V_2(p.u)	0,9992	0,98697	1,1	1,1	1,10	1,09062	1.0215	1.0295	1.0278
V_5(p.u)	1,01942	1,01648	1,01791	1,0972	1,0938	1,05265	1.0092	1.0145	1.0155
V_8(p.u)	1,02089	1,00488	0,99987	1,1	1,1	1,1	1.0044	1.009	1.0035
V_{11}(p.u)	0,95	1,07714	0,95	1,1	1,0965	1,0993	1.0797	1.0241	1.0397
V_{13}(p.u)	1,02784	1,01018	0,95	1,1	1,0893	1,1	0.9844	0.9835	0.9967
Qc_{10}(Mvar)	0	5	5	3,8290	5	0,6894	0	5	5
Qc_{12}(Mvar)	0	0,653251	5	0,43406	2,1264	1,8428	5	2.1588	0
Qc_{15}(Mvar)	5	5	5	0,719216	1,63571	0	4.9985	5	0
Qc_{17}(Mvar)	0,19950	0,3005	3,1797	0,06121	0,26005	1,0263	0	0.0767	0
Qc_{20}(Mvar)	5	5	5	0	1,03557	1,5686	5	5	5
Qc_{21}(Mvar)	5	5	5	0,15018	0,87403	3,2691	5	5	5
Qc_{23}(Mvar)	5	5	5	0,32163	4,9016	3,2912	4.9587	0	5
Qc_{24}(Mvar)	5	5	5	0	0,02547	0,37706	5	5	5
Qc_{29}(Mvar)	1,32783	5	4,9996	0,31831	0	1,17857	0	1.6478	5
T_{6-9}	0,948693	1,09999	0,9	0,9798	0,99560	0,994241	1.0888	1.0403	1.0596
T_{6-10}	0,9	0,9	0,9914	0,9	0,901703	0,943883	0.9	0.9	0.9
T_{4-12}	1,009	0,9799	0,9	0,9631	0,95761	0,95774	0.9451	0.9228	0.9303
T_{28-27}	0,9575	0,97486	0,9732	0,9547	0,95759	0,95454	0.9487	0.9613	0.9797
Fuel cost ($/h)	922.6860	970.444	995.8061	827.8445	843.8780	835.5524	**803.6357**	**803.6580**	**803.7306**
VD	**0.0899**	**0.0909**	**0.1132**	1.89997	1.987	1.8847	**0.1045**	**0.1117**	**0.1066**
$L_{\max}$	0.14793	0.14890	0.1495	**0.1241**	**0.12425**	**0.1243**	0.1468	0.1480	0.1490
Emission (ton/h)	0.2292	0.2074	0.2097	0.30292	0.27293	0.3023	0.3637	0.3635	0.3677
$p_{loss}(MW)$	6.04362	4.2713	8.6899	8.03501	7.2953	7.1225	9.8452	9.8300	9.9274

Table 4.5. Comparison of the results obtained for Case 4 to Case 6.

Case 4		Case 5		Cas6		
Algorithms	VD (pu)	Algorithms	$L_{\max}$	Algorithms	Fuel cost ($/h)	VD (p.u)
CS-KHA^1	**0.0899**	CSKHA	**0.1241**	CS-KHA	**803.6357**	**0.1045**
KHA	**0.0909**	KHA	**0.12425**	KHA	**803.6580**	**0.1117**
CS	**0.1132**	CS	**0.1243**	CS	**803.7306**	**0.1066**
CS-KHA ^{2}	**0.0902**	CSKHA	**0.1241**	CS-KHA	**803.6401**	**0.1046**
GSA[11]	0.093269	SKH[14]	0.1366	BHBO[4]	804.5975	0.1262
BBO[12]	0.1020	GEM[15]	0.1257	BSA [6]	803.4294	0.1147
DE[13]	0.0939	DE[13]	0.1243	MSA[7]	803.3125	0.10842
				MFO[7]	803.7911	0.10563
				FPA[7]	803.6638	0.13659

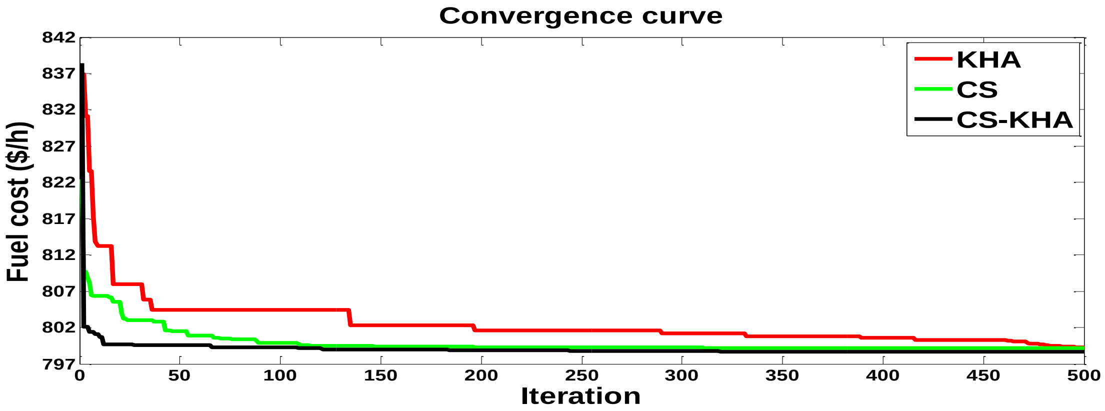

Figure 4.6a. Convergence curves of case 7

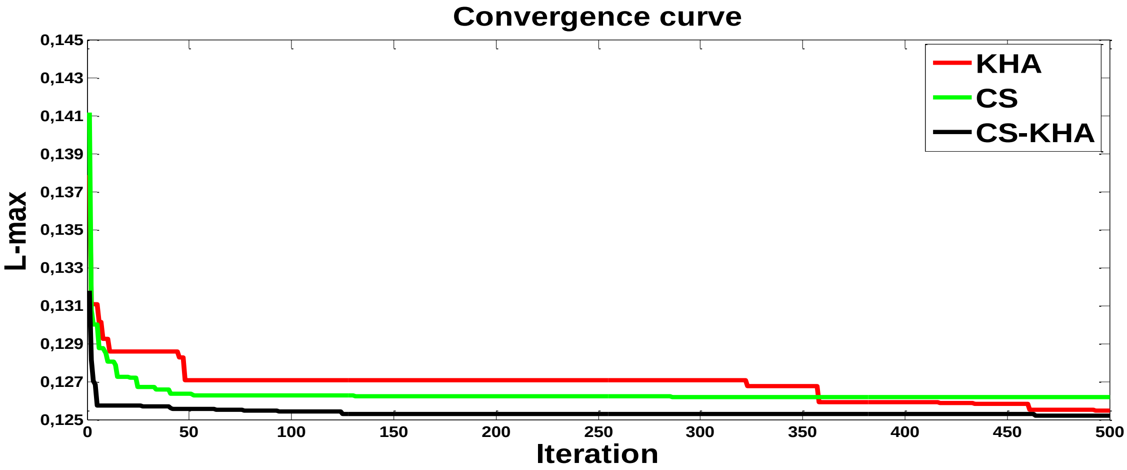

Figure 4.6b. Convergence curves of case 7

4.3.5 Case 8: Minimization of fuel cost and emission

Electrical power generation from conventional sources of energy emits hazardous gases into the environment. The quantity of sulfur oxides (SO_X), nitrogen oxides (NO_X) emission in tons per *hr* (*t/h*) is higher with the rise in generated power (in p.u. *MW*) next to the relationship presented in Eq. (4.11).

$$f\left(x,u\right)=emission=\sum_{i=1}^{NG}\left[\left(\alpha_i+\beta_i P_{G_i}+\gamma_i P_{G_i}^2\right)\times 0.01+\omega_i e^{\left(\mu_i P_{G_i}\right)}\right] \tag{4.11}$$

Where α_i, β_i, γ_i, ω_i and μ_i are all emission coefficients provided in [16]. The objective function for this case is assumed by Eq. (4.12):

$$f\left(x,u\right)=\left(\sum_{i=1}^{NG}a_i+b_i P_{G_i}+c_i P_{G_i}^2\right)+\lambda_E\times emission \tag{4.12}$$

The weight factors are selected as λ_E = 100 in this case.

The results yielded after optimization applied the CS-KHA technique are presented in Table 4.6 and the trend of optimization is shown in Figure 4.7. The results appear that the emission has been decreased from (**0.3685** ton/h) to (**0.2421**ton/h), Thus, the total fuel cost has augmented from (**799.0595**$/h) to (**835.3821**$/h) i.e. by 4.34% compared with Case 1, and the results obtained are compared with other techniques as shown in Table 4.7.

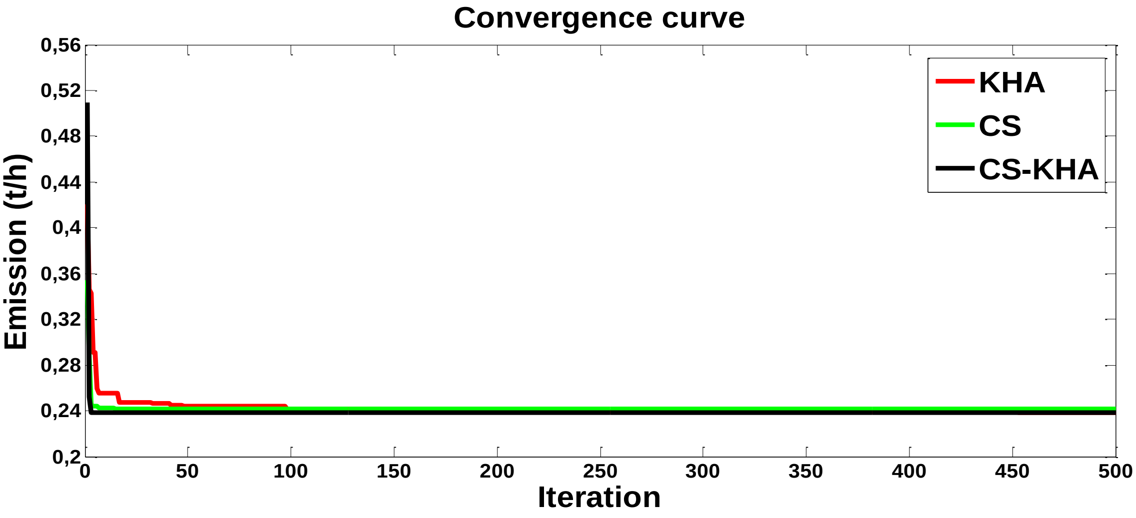

Figure 4.7. Convergence curves of case 8

4.3.9 Case 9: Minimisation fuel cost and active power losses

In this case, the goal of the OPF problem is to decrease the active power loss, which can be described as follows:

$$P_{loss} = \sum_{i=1}^{nl} \sum_{j=1, j\neq i}^{nl} G_{ij} \left[V_i^2 + V_j^2 - 2V_i V_j \cos\left(\delta_{ij}\right)\right] \tag{4.13}$$

A multi-objective case that aims at reducing fuel cost and active power loss simultaneously is transformed into single objective as:

$$f\left(x,u\right) = \sum_{i=1}^{NG} a_i + b_i P_{G_i} + c_i P_{G_i}^2 + \lambda_p \times P_{loss} \tag{4.14}$$

Where λ_p =40, the optimal settings of control variables are given in Table 4.6. The fuel cost has minimized to **859.149306 $/h** and total active power transmission losses has dramatically decreased to (**4.52652** MW). However, the propose CS-KHA obtained better results compared with techniques.

Table 4.6. Optimal settings of the control variables for case 7 to case 9.

Control variable	Case 7			Case 8			Case 9		
	CS-KHA	KHA	CS	CS-KHA	KHA	CS	CS-KHA	KHA	CS
P_{G1} (MW)	178.3494	175.2915	178.5539	112.7779	112.9464	111.7271	102.4758	102.0901	95.6030
P_{G2} (MW)	48.2403	47.5274	48.9785	59.1035	58.7161	58.4399	55,6153	55,6422	52,109
P_{G5} (MW)	20.5650	22.4648	21.3404	28.0892	28.1822	27.3951	38,0962	38,0268	50
P_{G8} (MW)	20.3673	22.6681	21.5868	34.9991	35.0000	35.0000	35	35	35
P_{G11} (MW)	12.7147	11.7468	10.0000	26.5804	27.1184	30.0000	30	30	30
P_{G13} (MW)	12.0000	12.3124	12.0000	26.9020	26.6188	26.2425	26,7392	27,1756	24,7444
V_1(p.u)	1.1000	1.1000	1.1000	1.1000	1.1000	1.1000	1,06746	1,06656	1,06054
V_2(p.u)	1.0892	1.0937	1.0829	1.0928	1.0924	1.1000	1,05695	1,056	1,05067
V_5(p.u)	1.0665	1.0674	1.0513	1.0696	1.0688	1.0806	1,03377	1,03314	1,03023
V_8(p.u)	1.0742	1.0825	1.0544	1.0798	1.0800	1.1000	1,04217	1,04034	1,03573
V_{11}(p.u)	1.0999	1.0999	1.1000	1.0992	1.0996	0.9000	1,08122	1,08432	1,03709
V_{13}(p.u)	1.1000	1.0982	1.1000	1.1000	1.0900	1.1000	1,0572	1,05351	1,07017
Qc_{10}(Mvar)	4.8864	1.6654	5.0000	1.1530	1.1760	5.0000	1,393e-05	0,00582	5
Qc_{12}(Mvar)	0.7211	2.2254	5.0000	3.3798	2.9034	5.0000	0,056116	5	4,9999
Qc_{15}(Mvar)	0.0187	0.9965	0	5.0000	1.5069	5.0000	3,89779	3,59704	5
Qc_{17}(Mvar)	0.6251	2.9405	0	3.7785	0.2768	5.0000	4,99982	5	5
Qc_{20}(Mvar)	0.0525	0.0173	0.8864	4.1506	1.0711	5.0000	4,99943	3,3517	0
Qc_{21}(Mvar)	0.8977	0.3830	5.0000	1.1979	0.7196	5.0000	5	5	5
Qc_{23}(Mvar)	2.4613	0.1354	0	0.0935	0.9665	5.0000	2,89363	3,27821	5
Qc_{24}(Mvar)	4.0616	3.2836	5.0000	5.0000	0.2050	5.0000	5	5	5
Qc_{29}(Mvar)	0.3548	0.8722	5.0000	1.4504	0.3080	5.0000	2,32625	5	5
T_{6-9}	0.9910	0.9888	0.9000	1.0603	1.0374	1.0772	1,0222	1,07066	0,9286
T_{6-10}	0.9055	0.9503	1.1000	0.9000	0.9597	0.9000	0,945857	0,9	1,1
T_{4-12}	0.9696	0.9850	1.1000	1.0186	1.0330	1.1000	0,990054	0,99436	1,1
T_{28-27}	0.9417	0.9446	0.9358	0.9818	0.9857	1.1000	0,973538	0,983613	0,99999
Fuel cost ($/h)	**799.5625**	**799.8928**	**800.3034**	**835.3821**	**835.9164**	**839.0130**	**859.1493**	**859.6794**	**864.4470**
VD	1.8465	1.7461	1.4380	1.6529	1.1912	0.8867	0.941279	0.93051	0.9860
$L_{\max}$	**0.1251**	**0.1253**	**0.1268**	0.1300	0.1342	0.1487	0.137761	0.13795	0.14408
Emission (ton/h)	0.3696	0.3608	0.3708	**0.2421**	**0.2422**	**0.2404**	0.228803	0.22836	0.22210
$p_{loss}(MW)$	8.8367	8.6110	9.0596	5.0521	5.1820	5.4047	**4.52652**	**4.5347**	**4. 5645**

Table 4.7. Comparison of the results obtained for Case 7 to Case 9.

Case 7			Case 8			Case 9		
Algorithms	Fuel cost ($ /h)	$L_{\max}$	Algorithms	Fuel cost ($ /h)	Algorithms	Fuel cost($/h)	Ploss (MW)
CS-KHA^1	**799.5625**	**0.1251**	CS-KHA^1	**835.3821**	CS-KHA^1	**859.149306**	**4.52652**
KHA	**799.8928**	**0.1253**	KHA	**835.9164**	KHA	**859.67941**	**4.5347**
CS	**800.3034**	**0.1268**	CS	**839.0130**	CS	**864.4470**	**4. 5645**
CS-KHA^2	**799.5683**	**0.1251**	CS-KHA^2	**835.3907**	CS-KHA^2	**859.14938**	**4.52653**
Gbest-ABC[17]	801.5821	0.1370	BSA [6]	835.0199	FPA [7]	859.1915	4.5404
MSA [7]	801.2248	0.13713	GA-MPC[18]	835.0420	MSA[7]	855.2706	4.7981
BSA[6]	800.3340	0.1259	MOGWO [16]	833.8528	MFO[7]	858.5812	4.5772

4.3.10. Triple- objective cases

There are three cases for triple objective in table 4.8, they can explain how the proposed CS-KHA method can give the best results.

4.3.11. Case 10: Minimization of fuel cost, active power losses and voltage deviation

In these case study three objectives, fuel cost, voltage deviation and active power loss are whole minimizing simultaneously. Its can be formulated as:

$$f\left(x,u\right)=\left(\sum_{i=1}^{NG}a_i+b_iP_{G_i}+c_iP_{G_i}^2\right)+\lambda_{VD}\times VD+\lambda_p\times P_{loss} \tag{4.15}$$

Where λ_p =40 and λ_{VD} =100, The CS-KHA method has been utilized to find to study the performance of the CS-KHA technique, three various objectives, namely, decreasing the cost of fuel, active power losses and voltage deviation are deliberated individually. The results of the simulation involve the optimal adjustment of the control variables yielded by the suggested method for four individual objectives are given in table 4.8, and table 4.9 display a comparison of whole techniques. Employing the CS-KHA, the fuel cost, the active power losses and the resulting voltage deviation get are **(864.2686)**, (**4.5449**) and **(0.3160)** respectively. The CS-KHA technique is more efficient than series CS-KHA, CS and KHA methods for solving a multi-objective OPF problem.

4.3.12 Case 11: Minimization of fuel cost, active power losses and emission

This case studied in this paper is the basic optimized three objectives, which includes minimizing the fuel cost , power losses and emission simultaneously . Hence, the objective function in this case is given as follows:

$$f\left(x,u\right)=\left(\sum_{i=1}^{NG}a_i+b_iP_{G_i}+c_iP_{G_i}^2\right)+\lambda_E\times Emission+\lambda_p\times P_{loss} \tag{4.16}$$

The CS-KHA method has been utilized to find the optimal solution of the problem. The optimal parameters of the control variables are presented in table 8.4 Employ the CS-KHA, the fuel cost, the emission and active power losses get are (**865.1805**), (**0.2242**) and (**4.0929**) respectively. There is evidence that by minimizing the objective function, the proposed method is superior to many methods used to solve the OPF problem.

4.3.13 Case 12: Minimization of fuel cost, voltage profile and emission

The multi-objective case of reduce the fuel cost, emission and voltage deviation is transformed into a single objective by multiplying a weighting factor to emission and voltage deviation. This objective functions of this case:

$$f\left(x,u\right)=\left(\sum_{i=1}^{NG}a_i+b_iP_{G_i}+c_iP_{G_i}^2\right)+\lambda_E\times Emission+\lambda_{VD}\times VD \tag{4.17}$$

Where λ_{VD} =100 and λ_E =100. In this case, minimization fuel cost with emission and voltage deviation offered by equation (4.18) is reduced by optimizing the system control parameters within the constraints Applied the suggested CS-KHA technique and the results are presented in table 3. The outcomes are compared with the optimization techniques when the results compared, Referred to case 12 in this study given the best proposed CS-KHA method related to original CS, KHA. we see that the suggested technique converge towards a better result than other techniques . The fuel cost, emission and voltage deviation values is yielded 804.3316 $/h and 0.3462 and 0.1640 respectively by applied the suggested CS-KHA. CS-KHA method which proves its ability to solve fuel cost with voltage deviation and emission minimization problem.

Table. 4.8 Simulation results of Cases 10-12 for IEEE 30-bus "Triple- objective"

Control variables	Case 10			Case 11			Case 12		
	CSKHA	KHA	CS	CSKHA	KHA	CS	CSKHA	KHA	CS
P_{G1} (MW)	104.5249	103.6928	92.2916	98.6974	101.6085	99.2209	164.8395	171.9780	170.5089
P_{G2} (MW)	54,3465	60,1612	80	58,2128	57,9613	57,0744	51,0948	50,0272	50,163
P_{G5} (MW)	37,5565	37,6539	39,0554	37,18	38,172	37,9333	20,9464	21,6641	22,0783
P_{G8} (MW)	35	34,9371	35	34,9784	35	35	29,0814	19,3606	24,756
P_{G11}(MW)	29,552	29,2022	30	30	29,1664	30	14,474	13,3601	13,3693
P_{G13}(MW)	27,0993	22,4509	12	28,5467	25,8985	28,416	12,0704	16,6763	12
V_1(p.u)	1,0775	1,08719	1,03794	1,1	1,1	1,1	1,03341	1,04002	1,05004
V_2(p.u)	1,06822	1,07534	1,02861	1,09406	1,09382	1,1	1,02503	1,02543	1,0323
V_5(p.u)	1,04122	1,04965	1,00398	1,07409	1,07592	1,08332	1,01103	1,01287	1,01456
V_8(p.u)	1,05056	1,05908	1,0077	1,08375	1,08514	1,1	1,00966	1,01041	1,00056
V_{11}(p.u)	1,0509	1,01307	1,1	1,1	1,07998	1,1	0,965062	1,02139	1,1
V_{13}(p.u)	1,05035	1,02317	1,00886	1,1	1,09512	1,1	1,04925	1,02575	0,96395
Qc_{10}Mvar	0,547088	2,48952	0	0,517852	1,41305	5	4,02246	0,813656	5
Qc_{12}Mvar	0,541429	0,48187	0	4,16862	0,155202	5	3,30099	0,240844	0
Qc_{15}Mvar	0,37127	4,41094	5	3,58793	0,839854	5	0,0722517	0,0261514	5
Qc_{17}Mvar	0,240534	4,49072	5	0,0732118	0,0010985	5	4,33627	1,23798	6,24743e-5
Qc_{20}Mbar	1,28399	3,43958	0	0,183157	0,257416	5	0,611775	1,94455	5
Qc_{21}Mvar	5	1,64497	0	5	4,84557	5	3,53858	1,31868	0
Qc_{23}Mvar	0,282304	4,63854	5	3,56207	1,56623	0	2,53085	1,80759	5
Qc_{24}Mvar	4,35843	1,2643	5	5	0,826752	5	5	3,95045	5

Qc_{29}Mvar	4,55509	3,57261	5	0,0260956	0,151317	2,32748	0,124265	0,749414	5
$T_{6\text{–}9}$	1,02249	1,06886	1,10	1,04433	1,07137	0,960578	0,980393	0,941706	1,1
$T_{6\text{–}10}$	1,01075	0,941228	0,9	0,904343	0,929703	1,1	0,90109	0,960605	0,9
$T_{4\text{–}12}$	1,06587	1,0464	0,97716	1,02222	1,06521	1,01044	1,0131	0,969156	0,9
$T_{28\text{–}27}$	1,0215	1,01662	0,985528	0,976679	0,993255	0,990608	0,946766	0,950057	0,979028
Fuel cost ($/h)	**856.6384**	**855.1997**	**865.9793**	**861.0731**	**858.5942**	**862.0141**	**804.1262**	**804.7822**	**804.1523**
VD	**0.3521**	**0.3966**	**0.3671**	1.6910	1.1325	1.8951	**0.1568**	**0.1682**	**0.1101**
$L_{\max}$	0.1471	0.1462	0.1483	0.1293	0.1350	0.1279	0.1463	0.1466	0.1489
Emission (ton/h)	0.2306	0.2322	0.2336	**0.2256**	**0.2288**	**0.2258**	**0.3347**	**0.3509**	**0.3483**
$p_{loss}(MW)$	**4.6792**	**4.6981**	**4.9581**	**4.2153**	**4.4068**	**4.2447**	9.1065	9.6663	9.4755

Table 4.9. Comparison studies Triple- objective cases

		CS	KHA	CSKHA^1	CSKHA^2
Case 10	Fuel cost ($/h), F1	**865.9793**	**855.1997**	**856.6384**	**856.6387**
	Power loss, F2	**4.9581**	**4.6981**	**4.6792**	**4.6795**
	VD, F3	**0.3671**	**0.3966**	**0.3521**	**0.3526**
Case 11		**CS**	**KHA**	**CSKHA^1**	**CSKHA^2**
	Fuel cost ($/h), F1	**862.0141**	**858.5942**	**861.0731**	**861.0733**
	Power loss, F2	**4.2153**	**4.4068**	**4.2447**	**4.2449**
	Fuel emission, F4	**0.2258**	**0.2288**	**0.2256**	**0.2258**
Case 12		**CS**	**KHA**	**CSKHA^1**	**CSKHA^2**
	Fuel cost ($/h),	**804.1523**	**804.7822**	**804.1262**	**804.1263**
	VD	**0.1568**	**0.1682**	**0.1101**	**0.1104**
	Fuel emission,	**0.3347**	**0.3509**	**0.3483**	**0.3485**

4.3.14 Fourth- objective cases

In Case 13, all the four competing objectives are considered "minimization of fuel cost, emission, power losses and voltage deviation". Referred to case 13 in this study, Table 4.10 represents the best proposed CS-KHA method related to five updated methods.

4.3.15 Case 13: minimization of cost, emission, voltage deviation and losses

In this case study four objectives, fuel cost, emission, voltage deviation and active power loss are whole reduced simultaneously. Its can be formulated as:

$$f\left(x,u\right)=\left(\sum_{i=1}^{NG} a_i+b_i P_{G_i}+c_i P_{G_i}^2\right)+\lambda_E\times Emission+\lambda_{VD}\times VD+\lambda_p\times P_{loss} \qquad (4.18)$$

The weight factors are selected as in [16] with λ_E = 19, λ_{VD} = 21 and λ_p = 22 to balance among the objectives.

To study the performance of the CS-KHA technique, four various objectives, namely, decreasing the cost of fuel, emission, voltage differential and active power are deliberated individually. The results of the simulation involve the optimal adjustment of the control variables yielded by the suggested method for four individual objectives are given in table 4.10, and table 4.11 display a comparison of whole techniques.

The CS-KHA technique is more efficient than other methods for solving a multi-objective OPF problem. Based on the results of the simulation, the suggested CS-KHA technique is capable of providing optimal solutions optimized compared to the CS and KHA, methods for the multi-objective OPF problem taking into consideration the cost of fuel, emission, voltage gap and active power losses.

4.3.16 Fifth- objective cases

4.3.17 Case 14: minimization of cost, emission, voltage deviation, voltage stability and losses

In this case study four objectives, fuel cost, emission, voltage deviation, voltage stability and active power loss are whole reduced simultaneously. It can be formulated as:

$$f\left(x,u\right)=\left(\sum_{i=1}^{NG} a_i + b_i P_{G_i} + c_i P_{G_i}^{2}\right) + \lambda_E \times Emission + \lambda_{VD} \times VD + \lambda_p \times P_{loss} + \lambda_L \times L_{\max} \tag{4.19}$$

There is a verification by lase case which deals with fifth objectives. The result illustrates that, the proposed methodology CS-KHA is the preferable in deciding the lowest objective values as shown in table 4.10 'case 14".

Table. 4.10 Simulation results of Case 13" Quad –objective" and case 14 " Fifth objective" for IEEE 30-bus

Control variables	Case 13			Case 14		
	CS	KHA	CS-KHA	CS	KHA	CS-KHA
P_{G1} (MW)	130.0107	129.8686	125.8615	124.4290	122.5765	125.4081
P_{G2} (MW)	53,8728	54,8287	51,1138	53,2175	56,0972	53,0698
P_{G5} (MW)	31,122	30,9348	31,0402	30,4865	33,0303	30,7882
P_{G8} (MW)	35	35	34,9807	35	33,5087	34,9561
P_{G11} (MW)	27,1396	15,9742	24,7056	25,2413	26,1787	25,3617
P_{G13} (MW)	12	22,6765	21,2074	20,7207	17,4607	19,36
V_1 (p.u)	1,1	1,1	1,1	1,1	1,1	1,1
V_2 (p.u)	1,08825	1,0887	1,08917	1,1	1,08832	1,08885
V_5 (p.u)	1,06287	1,06321	1,06405	1,0734	1,06148	1,064220

V_8 (p.u)	1,071530	1,07204	1,07205	1,08022	1,06977	1,07028
V_{11} (p.u)	1,05639	1,0702	1,05293	1,1	1,03026	1,05652
V_{13} (p.u)	1,01739	1,05011	1,02568	1,1	1,04997	1,03866
Qc_{10}(Mvar)	5	0	0,454755	5	4,9437	3,30446
Qc_{12}(Mvar)	5	2,05387	0,72323	0	0,270158	2,6025
Qc_{15}(Mvar)	3,3952	0,975567	3,32038	0	0,571056	2,92425
Qc_{17}(Mvar)	5	0,02654	1,76161	0	0,0167224	3,61804
Qc_{20}(Mvar)	4,99997	3,33051	4,76834	0	0,343435	0,906447
Qc_{21}(Mvar)	0	2,37481	3,62672	4,16327	0,870541	3,32206
Qc_{23}(Mvar)	5	1,4263	5	0	3,14292	0,210252
Qc_{24}(Mvar)	5	3,99204	5	5	4,95059	5
Qc_{29}(Mvar)	5	2,01571	2,23243	1,46134	1,84172	0
T_{6-9}	1,03445	0,999754	1,09786	1,1	1,07621	1,06593
T_{6-10}	1,1	1,09906	0,998356	1,1	0,971239	1,01257
T_{4-12}	1,06529	1,09087	1,07476	1,1	1,08476	1,06631
T_{28-27}	1,04599	1,02786	1,02953	1,04267	1,02415	1,01603
Fuel cost ($/h)	**825.5314**	**823.4412**	822.6903	**826.6999**	**825.8963**	**825.3990**
VD	**0.4836**	**0.4964**	**0.4654**	**0.6692**	**0.5393**	**0.5193**
Lmax	0.1466	0.1453	0.1456	**0.1440**	**0.1454**	**0.1445**
Emission(ton/h)	**0.2666**	**0.2660**	**0.2580**	**0.2565**	**0.2549**	**0.2581**
Ploss (MW)	**5.7451**	**5.8828**	**5.5092**	**5.6950**	**5.4521**	**5.5439**

Table 4.11, Comparison studies Quad and Fifth objective cases for multi method

		MOMICA [19],	MSA [7],	DE [13]	CS	KHA	CS-KHA^1	CS-KHA^2
Case 13	Fuel cost ($/h), F1	830.1884	830.639	830.2123	**825.5314**	**823.4412**	**822.6903**	**822.6905**
	Power loss, F2	5.5851	5.6219	5.5857	**5.7451**	**5.8828**	**5.5092**	**5.5094**
	VD, F3	0.2978	0.29385	0.29615	**0.4836**	**0.4964**	**0.4654**	**0.4657**
	Fuel emission, F4	0.2523	0.25258	0.25294	**0.2666**	**0.2660**	**0.2580**	**0.2583**
Case 14					CS	KHA	**CSKHA^1**	**CSKHA^2**
	Fuel cost ($/h), F1	-	-	-	**826.6999**	**825.8963**	**825.3990**	**825.3995**
	Power loss, F2	-	-	-	**5.6950**	**5.4521**	**5.5439**	**5.5442**
	VD, F3	-	-	-	**0.6692**	**0.5393**	**0.5193**	**0.5197**
	Fuel emission, F4	-	-	-	**0.2565**	**0.2549**	**0.2581**	**0.2582**
	L max, F5	-	-	-	0.2500	0.1454	**0.1454**	**0.1455**

In this part, a new hybrid technique called CS-KHA is applied to solve OPF problems. Test system fourteen cases have been studied in order to evaluate the performance of the suggested technique. The OPF problem was reported as a non-linear optimization problem with equality and inequality constraints.

Where several objective functions have been considered to minimize the fuel cost, to improve the voltage profile, and to enhance the voltage stability. However, the yielded results have been compared to those yielded using standard optimization techniques such as CS, KHA. The essential conclusion that can be extracted from this work is that the CS-KHA is a very efficient and robust technique for solving OPF problems.

It has perfect convergence characteristics and can be realized better effectiveness than some well-known optimization techniques. A comparison of the results yielded from CS-KHA and other techniques confirm the superiority of the algorithm for the suggested CS-KHA on stochastic methods in terms of solution efficiency for the OPF problems.

4.3.18. Comments and findings

The parallel hybrid CS-KHA method has overcome a significant disadvantage of the hybrid CS-KHA series technique over all cases, namely the necessity to provide an appropriate starting point. This drawback of the CS and KHA techniques was emphasized in the earlier study of authors because it makes any optimization technique based on a perfect selection of the initial point, more likely to get trapped in the local minima, although the significantly improved computation speed makes it possible to perform additional searches to increase confidence in the solution. The hybrid CS-KHA method, on the other hand, does not need the user to specify the starting point because it is automatically generated for the KHA step by the initial CS phase. In addition, the efficiency of the suggested hybrid technique improves with augmentation the objectives function.

In general, the suggested hybrid parallel technique has been shown to perform highly well in solving the optimal power flow problem.

4.4 IEEE 57-bus test system

In order to exam the scalability of the suggested CS-KHA technique, a greater test system is take into account in this work, which is the IEEE 57-bus test system, The system consist of 7 generators on buses 1, 2, 3, 6, 8, 9 and 12 and 15 tap change transformers. The system's total real and reactive power demands are 12,508 p.u and 3,364 p.u on a 100 MVA basis. The minimum and maximum voltages for whole buses are taken as 0.95 pu and 1.1 pu, respectively. General system data of 57-bus system are given in [21]. The OPF problem is solved for whole the exam cases of the IEEE- 57 bus exam system applied hybrid CS-KHA algorithm.

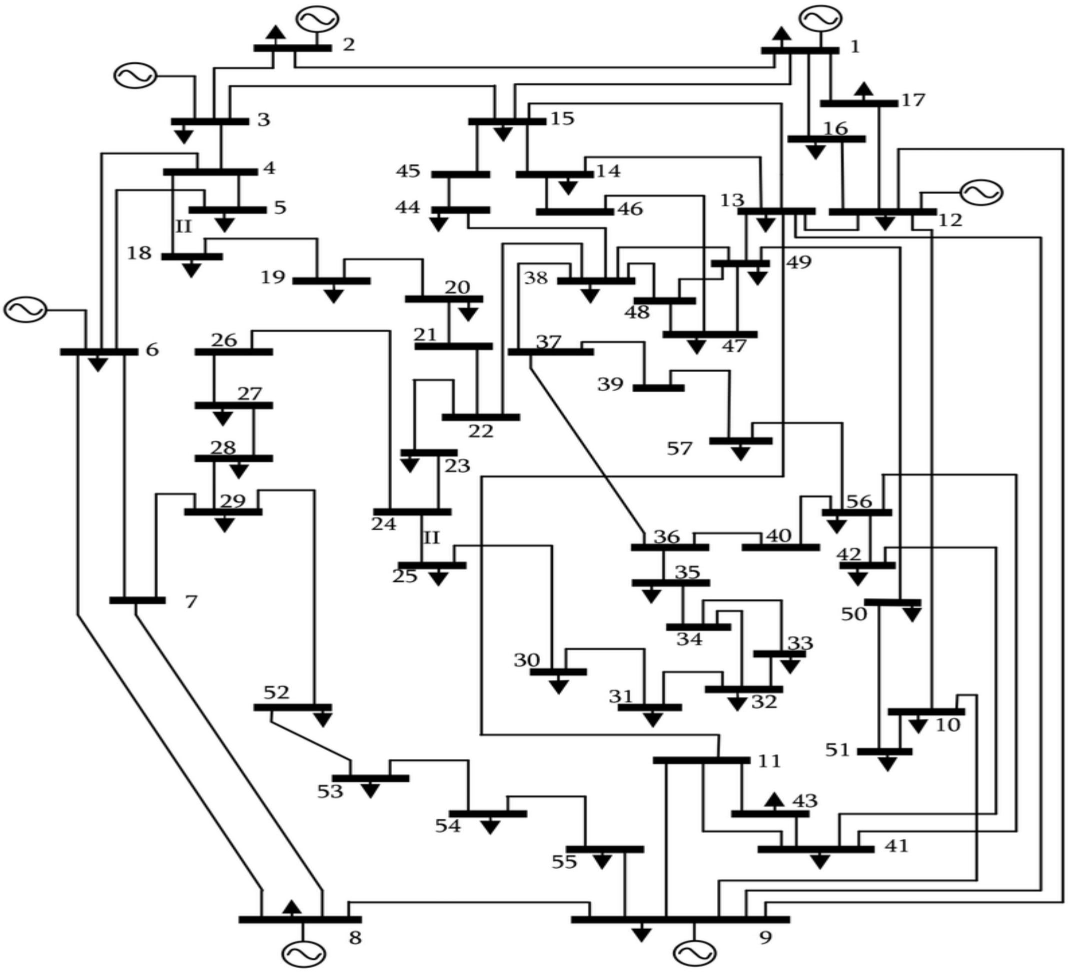

Figure 4.8 Single line diagram of IEEE-57 bus test system.

4.4.1 Case 15: Minimization of fuel cost

The goal of this case is to minimize the total generating fuel cost. Hence, the objective function of this case is presented by (4.2). The CS-KHA is run so as to find the optimal settings for this case and the gained results are presented in Table 4.12. The cost yielded for case 15 is (**41660.2273 $/h**).

4.4.2 Case 16: Minimization of voltage profile

In this case the suggested technique is applied to 57-bus test system so as to improve voltage deviation. The objective function is decrease to **0.5577** as given in table 4.12. The result comparison obtained by CS-KHA, KHA and CS with other algorithms are presented in table 4.13.

4.4.3 Case 17: Minimization of fuel cost and voltage deviation

The purpose of the objective function is to minimize simultaneously both fuel cost and voltage deviation. The converted single objective function next equation (4.8) with weight factor *w* is chosen as 100, the results of such optimization using the suggested CS-KHA technique are shown in Table 4.14. This table shows that the *VD* has been decrease from (**1.5991**p.u.) to (**0.6940** p.u.) compared with Case 15. Hence, the cost has slightly augmented from (**41660.2273 $/h**) to (**41712 $/h**) compared with Case 15.

4.4.4 Case 18: Minimization of fuel cost and voltage stability

In this case, multi-objective optimization, minimization voltage stability with the fuel cost provided by (4.10), where w_1 is selected as 100, is done by optimizing the control parameters of the system during the constraints by applied the suggested CS-KHA technique offered by Table 4.14. It can be seen that the suggested CS-KHA converges towards a better result than the KHA and CS technique by reduction the fuel cost to **41672.90764 $/h** and $L_{\max}$ to **0.2723**. The result comparison found by CS-KHA, KHA and CS with other techniques are presented in table 4.15.

Table 4.12. Optimum control variables for case 15 and case 16.

Control variable	Case 15			Case 16		
	CS-KHA	KHA	CS	CS-KHA	KHA	CS
PG1 (MW)	143.4297	145.0358	140.9221	471.9033	393.6098	513.6722
PG2 (MW)	87.0645	98.1294	77.7157	79,65695	98,6583	30
PG3 (MW)	45.1917	47.2053	40.0000	92,40007	57,84523	59,79458
PG6 (MW)	67.0035	54.0795	100.0000	46,79256	51,50391	30
PG8 (MW)	459.5789	472.6903	453.4311	232,8422	518,0421	550
PG9 (MW)	99.7951	81.2897	100.0000	99,24876	37,88237	30
PG12 (MW)	363.2292	367.0996	354.6953	266,034	131,7144	100
V1 (p.u)	1.0713	1.0695	1.0552	1,02237	1,023409	0,9967058
V2 (p.u)	1.0746	1.0734	1.0577	1,073999	1,062311	0,95
V3 (p.u)	1.0603	1.0611	1.0461	1,007648	1,016462	1,040492
V6 (p.u)	1.0597	1.0594	1.0654	1,004306	1,000456	0,995201
V8 (p.u)	1.0755	1.0778	1.1000	1,003906	1,010452	0,95
V9 (p.u)	1.0710	1.0699	1.0739	1,062235	1,030502	0,95
V12 (p.u)	1.0582	1.0562	1.0453	1,006495	1,005915	1,053807
Qc18(Mvar)	6.8293	4.8640	20.0000	6,695408	5,206463	0
Qc25(Mvar)	14.0936	16.3750	9.1658	19,37639	11,98027	10,38396
Qc53(Mvar)	11.2626	17.1950	20.0000	20	16,75879	14,5999
T4–18	1.0432	0.9608	0.9000	0,9137254	0,919320	0,9
T4–18	0.9543	1.0416	1.1000	1,071877	1,065802	1,1
T21–20	0.9981	1.0422	1.1000	0,9672907	0,9674481	0,96197
T24–25	1.0345	1.0436	1.1000	1,094638	0,9846575	0,9

T24–25	1.0039	1.0439	0.9000	1,032537	1,032989	1,1
T24–26	1.0175	1.0326	1.0668	1,003921	1,009034	0,9835
T7–29	0.9975	1.0014	1.0565	0,9862143	0,9758795	0,949235
T34–32	0.9533	0.9558	0.9000	0,9238578	0,9176231	0,9
T11–41	0.9016	0.9495	0.9000	0,9001775	0,9003361	0,9
T15–45	0.9869	0.9883	0.9795	0,9405974	0,9336218	0,97872
T14–46	0.9832	0.9756	0.9796	0,9852434	0,9603013	0,9
T10–51	0.9948	0.9876	0.9951	1,02096	0,9929484	0,9961529
T13–49	0.9579	0.9450	0.9000	0,90	0,9001134	0,9
T11–43	1.0219	0.9863	1.1000	0,973514	0,9786342	0,9
T40–56	0.9860	0.9959	1.1000	1,059415	0,9814492	0,9
T39–57	0.9993	0.9698	0.9869	0,925002	0,9207469	1,1
T9–55	1.0120	1.0285	1.1000	1,041118	1,007644	0,9
Fuel cost ($/h)	**41660.2273**	**41673.5922**	**41717.8801**	47374.0339	48063.3841	49505.0371
VD	1.5991	1.6959	1.7060	**0.5577**	**0.5861**	**0.6837**
$L_{\max}$	0.2816	0.2800	0.2775	0.3009	0.2973	0.2983
Emission (ton/h)	1.3566	1.4117	1.3269	1.7104	2.0093	2.7710
$p_{loss}(MW)$	14.4929	14.7297	15.9645	38.0779	38.4561	62.6668

Table 4.13. Comparison of the results obtained for Case 15 and Case 16.

Case 15		Case 16	
Algorithms	Fuel cost ($/h)	Algorithms	VD (p.u)
CS-KHA^1	41660.2273	CS-KHA^1	0.5577
KHA	41673.5922	KHA	0.5861
CS	41717.8801	CS	0.6837
CS-KHA^2	41660.2274	CS-KHA^2	0.5578
MSA [7]	41673.7231	APFPA [20]	0.8909
ICBO [8]	41697.3324	DE[13]	0.59267
DE [22]	41667.82		

Table 4.14. Optimum control variables for case 17 and case 18.

Control variable	Case 17			Case 18		
	CS-KHA	KHA	CS	CS-KHA	KHA	CS
PG1 (MW)	140.6795	141.9955	146.9150	145.63717	147.4252	140.62448
PG2 (MW)	94.9802	92.1514	100.0000	93,41317	70,41633	76,64457
PG3 (MW)	47.1461	45.7668	40.0000	43,60194	48,42804	40
PG6 (MW)	66.5315	78.1945	100.0000	66,58502	79,49157	42,59378
PG8 (MW)	460.6278	460.5117	478.9845	463,769	464,107	550
PG9 (MW)	94.4812	89.2280	30.0000	88,24593	90,86394	66,53411
PG12(MW)	362.1398	358.8398	371.7001	364,439	365,3286	352,9121
V1 (p.u)	1.0206	1.0198	1.1000	1,065714	1,071911	1,069522
V2 (p.u)	1.0244	1.0253	1.1000	1,06856	1,074518	1,071359
V3 (p.u)	1.0119	1.0155	1.1000	1,058032	1,064053	1,058788
V6 (p.u)	1.0150	1.0264	1.1000	1,059052	1,064469	1,056178
V8 (p.u)	1.0384	1.0503	1.1000	1,075125	1,080583	1,1
V9 (p.u)	1.0240	1.0329	1.1000	1,074043	1,075218	1,081988
V12 (p.u)	1.0040	1.0070	1.1000	1,058413	1,061121	1,06022
Qc18(Mvar)	10.8442	8.0117	0	8,100758	2,438026	20
Qc25(Mvar)	6.4490	15.9809	15.1607	13,05276	0,00061261	20
Qc53(Mvar)	13.4479	11.0521	20.0000	7,513088	2,218401	9,451008
T4–18	0.9583	1.0192	0.9000	1,029568	1,071517	0,93533
T4–18	1.0017	0.9868	1.1000	0,982612	0,927481	1,1
T21–20	0.9981	0.9773	1.1000	1,042477	0,9802909	0,9950
T24–25	0.9680	0.9543	0.9000	1,031908	0,9212172	1,1
T24–25	0.9574	1.0740	1.1000	1,023043	0,9427498	1,1

T24–26	1.0298	1.0136	1.0171	1,020643	1,042666	1,1
T7–29	0.9801	0.9951	1.0648	0,995707	0,9879004	1,057779
T34–32	0.9283	0.9354	0.9388	0,9010713	0,9012895	0,90000
T11–41	0.9000	0.9001	0.9000	0,9125124	0,9159888	0,9000041
T15–45	0.9509	0.9513	1.0178	0,9878071	0,9900062	0,9914929
T14–46	0.9527	0.9606	1.1000	0,9731593	0,9750129	0,9782907
T10–51	0.9725	0.9861	1.0697	0,993979	0,9966176	0,9959146
T13–49	0.9170	0.9177	0.9738	0,922972	0,9211986	0,9400298
T11–43	0.9418	0.9782	1.1000	0,9913753	0,9861991	0,9988105
T40–56	1.0432	0.9771	0.9000	1,082166	0,9970617	1,1
T39–57	0.9218	0.9373	1.1000	0,9170872	1,090158	0,94974
T9–55	1.0029	1.0128	1.1000	1,016755	1,033347	1,10
Fuel cost ($/h)	**41712**	**41705**	**41791**	**41672.9076**	**41676.3189**	**41796.8012**
VD	**0.6940**	**0.7004**	**1.5878**	1.9022	1.8864	1.9760
Lmax	0.2931	0.2935	0.2870	**0.2723**	**0.2688**	**0.27802**
Emission (ton/h)	1.3554	1.3507	1.4690	1.3757	1.37908	1.68885
$p_{loss}(MW)$	15.7861	15.8877	16.8061	14.8914	15.2609	18.50979

Table 4.15. Comparison of the results obtained for Case 17 and Case 18.

Case 17			Case 18		
Algorithms	Fuel cost ($/h)	VD (p.u)	Algorithms	Fuel cost ($/h)	*Lmax*
CSKHA^1	41712	0.6940	CS-KHA^1	41672.90764	0.2723
KHA	41705	0.7004	KHA	41676.3189	0.2688
CS	41791	1.5878	CS	41796.8012	0.27802
CSKHA^2	41712.02	0.6941	CS-KHA^2	41672.90767	0.2724
MSA [7]	41714.9851	0.67818	MSA [7]	41675.9948	0.27481
ICBO [8]	41726.3758	0.69723	DE [13]	41667.53	0.28022
DE[22]	41697.50	0.77253			

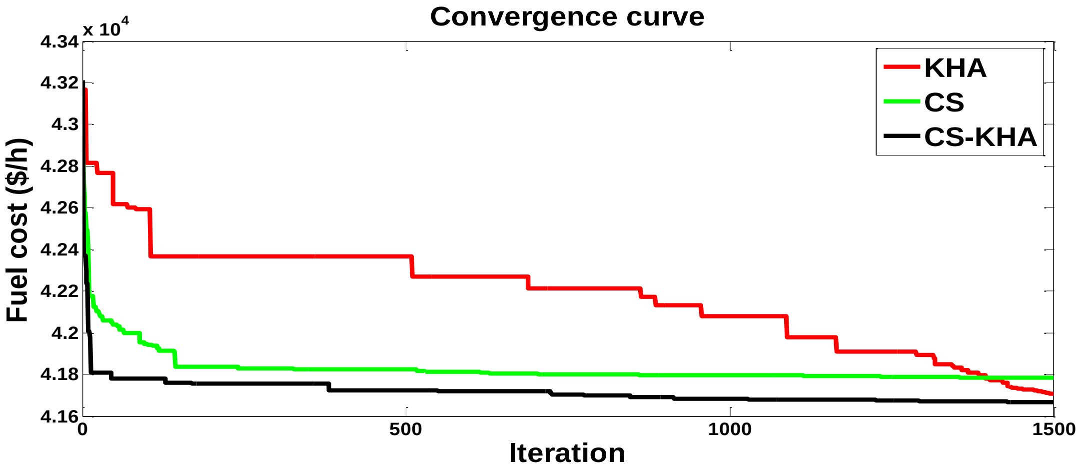

Figure 4.9. Objective function curve for Case 18.

4.4.5 Comments and findings

this work suggests a hybrid parallel (CS-KHA), the effectiveness of this technique is utilized to be compared with hybrid series (CS-KHA) and get a worldwide ideal solution, in addition, less computational time to achieve the ideal solution, local minima evasion, and speeder convergence, which make them adequate for viable applications for solving various constrained optimization problems.

It is clear from this study that hybrid parallel (CS-KHA) gives better results than hybrid series (CS-KHA) to solve OPF problem. And exam of system network IEEE 57-bus test systems.

4.5 Results of IEEE 118-bus test system

4.5.1Case 19: Fuel cost minimization

To prove performance of the suggested hybrid CS-KHA, the large-scale IEEE 118-bus system is deliberated for study goal, its essential characteristics are presented in [21]. In general, the efficiency of the proposed algorithm is excellent for variables' higher number in constrained optimization problems. Therefore, CS-KHA method is utilized for the system to decrease fuel cost. Hence, this case's objective function is presented by (4.2). The CS-KHA is implemented so as to get the optimal settings for this case and the gained results are presented in Table 4.16. In this case, minimizing the fuel cost's fundamental objective produce to a value of 135260.45$/h by CS-KHA, the most minimal when compared with other recent studies' substantial results as seen in Table 4.17.

Table 4.16. The control variables' optimal settings for case 19.

Control variables	CS-KHA	KHA	CS	**Control variables**	CS-KHA	KHA	CS
P_{G1}(MW)	366.9132	385.4828	368.0476	V_{G31}	1.0559	1.0328	1.0147
P_{G4}(MW)	30.0000	30.0000	40.4392	V_{G32}	1.0628	1.0410	1.0174
P_{G6}(MW)	30.8504	30.0000	30.0056	V_{G34}	1.0699	1.0429	1.0476
P_{G8}(MW)	30.0000	36.5892	30.5938	V_{G36}	1.0709	1.0615	1.0452
P_{G10}(MW)	32.1926	30.0951	30.6092	V_{G40}	1.0584	1.0335	1.0348
P_{G12}(MW)	322.0172	337.7073	298.7903	V_{G42}	1.0728	1.0407	1.0430
P_{G15}(MW)	66.9864	67.3679	73.6602	V_{G46}	1.0779	1.0699	1.0825
P_{G18}(MW)	34.9502	31.6466	34.1581	V_{G49}	1.0838	1.0856	1.0880
P_{G19}(MW)	30.0126	30.1197	34.9399	V_{G54}	1.0743	1.0686	1.0785
P_{G24}(MW)	31.2758	40.0241	32.0601	V_{G55}	1.0661	1.0609	1.0791
P_{G25}(MW)	30.0890	30.3142	30.7494	V_{G56}	1.0747	1.0669	1.0783
P_{G26}(MW)	152.1116	160.5087	124.9473	V_{G59}	1.0929	1.0880	1.0949
P_{G27}(MW)	210.4531	212.1246	213.9664	V_{G61}	1.0857	1.0959	1.0989
P_{G31}(MW)	30.0107	30.0000	32.9586	V_{G62}	1.0857	1.0980	1.0949
P_{G32}(MW)	32.1135	32.1022	32.1000	V_{G65}	1.0886	1.0891	1.0524
P_{G34}(MW)	30.1433	30.0000	30.0574	V_{G66}	1.0981	1.1000	1.0983

P_{G36}(MW)	30.9994	32.3755	37.3000	V_{G69}	1.0819	1.0947	1.0921
P_{G40}(MW)	37.2945	31.1420	39.2771	V_{G70}	1.0760	1.0680	1.0753
P_{G42}(MW)	32.7803	40.1303	32.0453	V_{G72}	1.0847	1.0782	1.0618
P_{G46}(MW)	30.5901	30.0504	61.3421	V_{G73}	1.0807	1.0823	1.0806
P_{G49}(MW)	35.7090	35.7110	35.7293	V_{G74}	1.0614	1.0721	1.0635
P_{G54}(MW)	150.1344	159.3915	147.9769	V_{G76}	1.0481	1.0534	1.0537
P_{G55}(MW)	45.0829	45.1069	46.4248	V_{G77}	1.0530	1.0533	1.0694
P_{G56}(MW)	30.2316	30.1951	30.0706	V_{G80}	1.0578	1.0871	1.0748
P_{G59}(MW)	41.1021	34.2682	31.4284	V_{G85}	1.0698	1.0849	1.0867
P_{G61}(MW)	128.9333	126.3616	116.7174	V_{G87}	1.0883	1.0856	1.0802
P_{G62}(MW)	119.4878	104.4463	108.5139	V_{G89}	1.0766	1.1000	1.0966
P_{G65}(MW)	30.0414	30.6740	33.8130	V_{G90}	1.0543	1.0908	1.0790
P_{G66}(MW)	274.4206	296.6764	274.6836	V_{G91}	1.0621	1.0926	1.0810
P_{G69}(MW)	290.2244	273.8381	285.3788	V_{G92}	1.0568	1.0932	1.0839
P_{G70}(MW)	33.8793	31.0321	30.0310	V_{G99}	1.0515	1.0699	1.0605
P_{G72}(MW)	30.0000	30.0000	30.5010	V_{G100}	1.0395	1.0786	1.0654
P_{G73}(MW)	35.0183	30.0011	34.5178	V_{G103}	1.0212	1.0726	1.0593
P_{G74}(MW)	30.0000	34.6584	30.0089	V_{G104}	1.0060	1.0641	1.0498
P_{G76}(MW)	31.1843	30.0000	30.0515	V_{G105}	1.0123	1.0751	1.0472
P_{G77}(MW)	30.8112	30.0330	35.3680	V_{G107}	0.9973	1.0717	1.0433
P_{G80}(MW)	353.3451	328.0506	339.0098	V_{G110}	0.9894	1.0791	1.0417
P_{G85}(MW)	30.4117	34.3764	30.0251	V_{G111}	0.9980	1.0890	1.0528
P_{G87}(MW)	31.2043	31.2010	31.2000	V_{G112}	0.9775	1.0721	1.0298
P_{G89}(MW)	373.0515	343.3753	383.0308	V_{G113}	1.0584	1.0584	1.0260
P_{G90}(MW)	30.0217	30.0053	30.0816	V_{G116}	1.0928	1.1000	1.0466
P_{G91}(MW)	30.1360	31.2499	33.4771	Qc_{5} (Mvar)	1.0968	0.1341	0.4603
P_{G92}(MW)	30.0000	31.6228	30.0239	Qc_{34}(Mvar)	0.0395	0.0656	7.8806
P_{G99}(MW)	31.5839	30.1290	32.1729	Qc_{37}(Mvar)	1.7660	7.3596	2.7258
P_{G100}(MW)	161.0126	174.5208	163.4482	Qc_{44}(Mvar)	10.4951	0.3568	0.0083
P_{G103}(MW)	42.2950	42.1514	42.2731	Qc_{45}(Mvar)	0.0001	2.6926	1.0940
P_{G104}(MW)	30.8340	31.1019	30.1950	Qc_{46}(Mvar)	6.3599	0.6672	17.7909
P_{G105}(MW)	30.1658	30.0082	30.0294	Qc_{48}(Mvar)	0.3103	0.6422	0.3959
P_{G107}(MW)	30.7389	30.1938	30.7178	Qc_{74}(Mvar)	0.5937	0.0949	12.9769
P_{G110}(MW)	32.0056	30.6153	30.4068	Qc_{79}(Mvar)	0.4359	1.0046	1.7815
P_{G111}(MW)	40.8006	40.8581	40.8015	Qc_{82}(Mvar)	2.6580	0	2.5440
P_{G112}(MW)	30.6941	30.1776	35.3112	Qc_{83}(Mvar)	2.7523	0	2.0127
P_{G113}(MW)	30.5556	30.1612	43.2123	Qc_{105}(Mvar)	1.1846	2.5892	10.9604
P_{G116}(MW)	31.5470	30.1511	30.6720	Qc_{107}(Mvar)	4.1717	0.0284	4.9321
V_{G1}	1.0322	1.0169	1.0043	Qc_{110}(Mvar)	4.0167	0.5725	0.0614
V_{G4}	1.0515	1.0342	1.0224	$T_{(8-5)}$	1.0269	1.0527	1.0180
V_{G6}	1.0349	1.0323	1.0137	$T_{(26-25)}$	1.0551	0.9293	1.0770
V_{G8}	1.0742	1.0906	1.0714	$T_{(30-17)}$	0.9923	1.0165	1.0267
V_{G10}	1.0786	1.0965	1.0833	$T_{(38-37)}$	0.9561	0.9903	0.9672
V_{G12}	1.0353	1.0238	1.0114	$T_{(63-59)}$	0.9402	0.9071	0.9072
V_{G15}	1.0383	1.0268	1.0176	$T_{(64-61)}$	1.0339	0.9722	0.9434
V_{G18}	1.0476	1.0328	1.0167	$T_{(65-66)}$	1.0317	1.0952	1.0250
V_{G19}	1.0464	1.0356	1.0192	$T_{(68-69)}$	1.0046	1.0947	0.9504
V_{G24}	1.0571	1.0634	1.0366	$T_{(81-80)}$	1.0284	0.9213	0.9667
V_{G25}	1.0939	1.0568	1.0337	**Fuel cost ($/h)**	**135260.45**	**135400.78**	**135610.321**
V_{G26}	1.0835	1.0689	1.0860	**Ploss(MW)**	**56.4548**	**58.1287**	**53.3527**
V_{G27}	1.0684	1.0325	1.0148				

Table 4.17. The results obtained are compared for Case 19.

Algorithms	Fuel cost ($/h)
CS-KHA[1]	135260.45
KHA	135400.78
CS	135610.321

CS-KHA^2	135260.46
BSA [6]	135333.4743
ABC 6]	135304.3584
BBO [6]	135262.7289

4.5.2 Comments and findings

We have study the performance of the hybrid both parallel and series CS-KHA technique, through experience and study of whole techniques. Turns out the hybrid parallel CS-KHA technique is more efficient than hybrid series and other methods for solving a multi-objective OPF problem, for multi-objective techniques. Based on the results of the simulation on test 118-bus test system, the suggested hybrid parallel CS-KHA technique is capable of providing optimal solutions optimized compared to the hybrid series CS-KHA. We conclude that the hybrid parallel CS-KHA technique is more efficient for in solving the multi-objective OPF problem taking into consideration the cost of Fuel, emission, voltage deviation and active power losses.

4.6 Conclusion

This chapter compares several of the updated techniques and employs the new hybrid CS-KHA. This technique has been tried in two different ways, first in the form of parallel and the other in series optimization methods to solve OPF "most significant power system optimization problems." This suggested method has been efficiency carry out the results through minimize the single and the multi-objective function is realized compared with other methods "accuracy ". Through 19 cases "14 in IEEE-30, 4 IEEE-57 and 1 in IEEE-118", the suggested techniques can verify the preferably techniques "better results" related to different updated studies described in literature. This method can reach a minimum objective by finding the optimum setting for system control variables. For larger scale, the implementation of the suggested methods is applied with high convergence speed and search ability and it ensures gaining suitable operating point for implement in the power systems.

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Chapter 5. Application of Hybrid CSKHA to ED problem

5.1 Introduction:

This chapter describes the efficiency of different meta-heuristic methods based on both hybrid parallel and series CSKHA technique to solve different types of ED problems, in order to estimate the finest power generation combinations in a given system at the minimum operating cost, while maintaining the system's operating conditions effectively.

The fuel cost is decreased by mainly based on power generation capacity constraints, power balance constraints and valve point load effects, to meet the non-linear operating conditions of the thermal unit. With regard to optimization, a comparative study of different meta-heuristic methods is carried out.

In order to prove the effectiveness and applicability of the suggested techniques and for the purpose of comparison, different types of ED problems are tested. The results of this survey offer that the suggested methods make it possible to find loads more economical than those specified by other techniques.

5.2 Applied CSKHA to the ED

The different steps to applied CS-KHA in ED are:

Step 1: Read characteristics of generation thermal units, Input the maximum number of iterations and population size.

Step 2: Use each of the next solutions to initialize random population X of generated power of the units within its boundaries.

$$P_m = P_m^{\min} + rand\,()\left(P_m^{\max} - P_m^{\min}\right) \tag{5.1}$$

The initial population obtained is X as next.

$$X = \begin{pmatrix} P_{11} & \cdots & P_{1N} \\ \vdots & \ddots & \vdots \\ P_{N_{POP}^{1}} & \cdots & P_{N_{POP}^{N}} \end{pmatrix} \tag{5.2}$$

Among them, $N\ pop$ is the population, n is the units’ number.

Step 3: Determine objective function applied in (2.1)

Step 4: Update the krill position by KU operator

Step 5: Destroy the worse krill and build new ones by KA operator

Step 6: Replace the KEEP worst krill with the KEEP best krill.

Step 7: Choose the best solution according to the fitness function evaluation.

Step 9: Return steps 3 through 7 until any termination conditions are met.

5.3 Results and discussion

CSKHA is used to solve the ED problems for three different cases to ensure its optimization effectiveness, where the objective function is restricted by the output boundaries of generation units and transmission losses. The efficiency of both parallel and series CSKHA is compared with different other optimization techniques. Simulations were carried out in the context of the MATLAB environment.

5.3.1 Test case 1: 3 generators

The system of 3 generating units with the load demand of [400,500,600,700] MW is utilized here. Whole data (maximum and lower limits for units and fuel cost coefficients are chosen as given in [1,2].The optimum solution yielded by any version of both hybrid parallel and series CSKHA technique is too listed while its total fuel cost is determined. Evidently, the suggested CSKHA^1 and CSKHA^2 technique are capable to obtain a solution with an optimum fuel cost, while the load demand constraint is met. In Figure 1, the conduct of CSKHA^1 contrast is seeing in terms of fuel cost relative to 3 generators. The figure display that CSKHA^1 had a quicker convergence. The results yielded by the suggested CSKHA^1 and CSKHA^2 method are compared them with each other and with other advanced techniques employing the same fuel-efficiency functions, abbreviated in table 1, and the comparative results are presented in table 2.

The preferable results are highlighted in bold characters. It should be aforementioned that almost whole comparison techniques were capable to get the minimum fuel cost as a result of the hybrid parallel CSKHA techniques better than hybrid series CSKHA technique.

Table 5.1. The optimal results get from the case 1.

PD (MW)	methods	P_1 (MW)	P_2 (MW)	P_3 (MW)	*Ploss*(MW)	Cost ($ /h)	Emission (t /h)
400	CS	102.4814	153.7944	151.1370	7.4127	29558.4239	200.2045
	KHA	102.4817	153.7941	151.1370	7.4127	29559.2962	200.2045
	CSKHA^1	102.4816	153.7942	151.1372	7.4125	29559.2960	200.2244
500	CS	128.7865	192.6146	190.2929	11.6937	39210.1941	311.1575
	KHA	128.7864	192.6147	190.2928	11.6937	39209.8207	311.1575

	CSKHA^1	128.7863	192.6149	190.2928	11.6937	39208.8873	311.1571
600	CS	155.4338	231.8096	229.7591	17.0020	50938.4092	461.2190
	KHA	155.4337	231.8095	229.7591	17.0020	50937.9479	461.2190
	CSKHA^1	155.4336	231.8095	229.7592	17.0020	50937.2561	461.2190
700	CS	182.4346	271.3891	269.5447	23.3680	64861.1615	651.5875
	KHA	182.4346	271.3892	269.5447	23.3680	64861.2919	651.5875
	CSKHA^1	182.4347	271.3891	269.5446	23.3680	64861.8783	651.5875

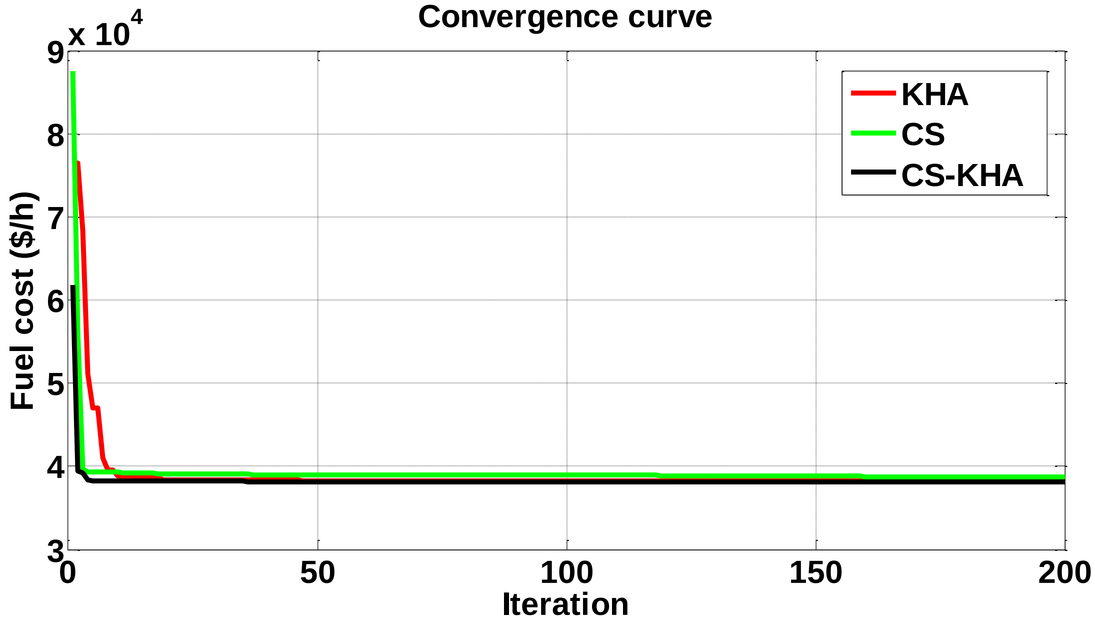

Figure.5.1.Convergence characteristics of case 1.

Table 5.2. Comparison of results for case 1

PD(MW)	methods	CS	KHA	CSKHA^1	CSKHA^2	GA[2]	PSO[2]	FPA[3]
400	Cost ($ /h)	29558.4239	29559.2962	29559.2960	29559.2961	29563.2	29559.9	29559.81
	Emission(t /h)	200.2045	200.2045	200.2044	200.2044	200.256	200.221	200.2238
	Ploss (MW)	7.4127	7.4127	7.4125	7.4127	7.41324	7.41173	7.4126
500	Cost ($ /h)	39210.1941	39209.8207	39208.8873	39208.8875	39220.1	39210.2	39210.15
	Emission(t /h)	311.1575	311.1575	311.1571	311.1571	311.273	311.15	311.155
	Ploss (MW)	11.6937	11.6937	11.6937	11.6938	11.6964	11.6919	11.6938
600	Methods (t /h)	CS	KHA	CSKHA	CSKHA	FA[4]	BA[4]	FA-BA[4]
	Cost ($ /h)	50938.4092	50937.9479	50937.2561	50937.2562	50937.31	50937.31	50937.29
	Emission	461.2190	461.2190	461.2190	461.2190	461.22	461.22	461.22
	Ploss (MW)	17.0020	17.0020	17.0020	17.0024	17.0022	17.0022	17.0022
700	Cost ($ /h)	64861.1615	64861.2919	64861.8783	64861.8784	64861.51	64861.52	64861.52
	Emission(t /h)	651.5875	651.5875	651.5875	651.5875	651.57	651.57	651.57
	Ploss (MW)	23.3680	23.3680	23.3680	23.3680	23.3664	23.3663	23.3663

5.3.2 Test case 2: 6 generators

This case examines a thermal system generating 6-units. The fuel cost's coefficients, the generators constraints and the matrixes of transmission loss coefficient are presented in [5.6]. Table 3 represent the products and cost functions related with the 6 generators power system and comparison of this technique with different techniques for [700, 800, 900, 1000] MW demands given in table 4. It can be noted that the suggested hybrid parallel CSKHA gives minimum values of cost function compared with hybrid series CSKHA and other techniques [5, 6]. Hybrid parallel CSKHA display the efficiency of fitness values and gets convincing and plausible results with augmented system dimensions. In addition, the constraints of the system are met.

Figure 5.2 agrees CSKHA ability to achieve the lowest cost in least iterations. Figure 5.2 display the excellence of the suggested technique to obtain a minimum cost compared to original KHA and CS.

Table 3.5. The optimal results get from the case 2.

	P_D =700 *(MW)*			P_D =800 *(MW)*		
Control Variables	CSKHA	KHA	CS	CSKHA	KHA	CS
P_1 *(MW)*	28,2906	28,2906	28,2969	32,5859	32,5858	32,588
P_2 *(MW)*	10	10	10	14,4839	14,4839	14,4931
P_3 *(MW)*	118,9573	118,9573	118,7832	141,5465	141,5464	141,6771
P_4 *(MW)*	118,6773	118,6773	118,5615	136,0459	136,0456	136,0898
P_5 *(MW)*	230,7626	230,7623	231,0278	257,6619	257,6619	257,6181
P_6 *(MW)*	212,7441	212,7443	212,7678	243,0068	243,0073	242,8600
Ploss (MW)	19,4318	19,4319	19,4372	25,3309	25,3309	25,3261
Cost *($/h)*	36912,1770	36912,1772	36912,1802	41896,6763	41896,6764	41896,6775
Emission *(t/h)*	501,0113	501,0112	501,1661	648,9859	648,9863	648,8948

	P_D =900 *(MW)*			P_D =1000 *(MW)*		
Control Variables	CSKHA	KHA	CS	CSKHA	KHA	CS
P_1 *(MW)*	36,848	36,8479	36,848	41,1656	41,1659	41,1655
P_2 *(MW)*	21,0772	21,0773	21,0796	27,7786	27,7785	27,7793
P_3 *(MW)*	163,9293	163,9294	163,9334	186,5593	186,5591	186,5644
P_4 *(MW)*	153,2286	153,2292	153,2296	170,5819	170,5818	170,5826
P_5 *(MW)*	284,1692	284,1691	284,1638	310,8291	310,8294	310,829
P_6 *(MW)*	272,7358	272,7351	272,7334	302,5678	302,5674	302,561
Ploss (MW)	31,9880	31,9881	31,9878	39,4818	39,4822	39,482
Cost *($/h)*	47045,2213	47045,2215	47045,2219	52361,2261	52361,2319	52361,2323
Emission *(t/h)*	821,9781	821,9777	821,9717	1022,4809	1022,481	1022,47757

Table 4.5. Comparison of results for case 2.

PD(MW)	methods	CSKHA^1	KHA	CS	CSKHA^2	FA [4]	BA [4]	FA-BA[4]
700	Cost ($ /h)	36912,1772	36912,1772	36912,1802	36912,1773	36912.19	36912.08	36912.19
	Emission(t/h)	501,0113	501,0112	501,1661	501,0114	501.02	501.02	501.08
	Ploss (MW)	19,4318	19,4319	19,4372	19,4319	19.4311	19.4324	19.4373
800	Cost ($ /h)	41896,676	41896,6764	41896,6775	41896,677	41896.69	41896.57	41896.69
	Emission(t /h)	648,9859	648,9863	648,8948	648,9859	649.00	648.98	648.98
	Ploss (MW)	25,3309	25,3309	25,3261	25,3311	25.3315	25.3306	25.3309
900	Cost ($ /h)	47045,2213	47045,2215	47045,2219	47045,2215	47045.24	47045.12	47045.24
	Emission(t /h)	821,9781	821,9777	821,9717	821,9783	821.97	821.98	821.98
	Ploss (MW)	31,9880	31,9881	31,9878	31,9881	31.9879	31.9882	31.9880

1000	Cost ($ /h)	52361,2261	52361,2319	52361,2323	52361,2262	52361.25	52361.12	52361.25
	Emission(t /h)	1022,4809	1022,481	1022,47757	1022,4809	1022.48	1022.46	1022.47
	Ploss (MW)	39,4818	39,4822	39,482	39,4819	39.4820	39.4813	39.4816

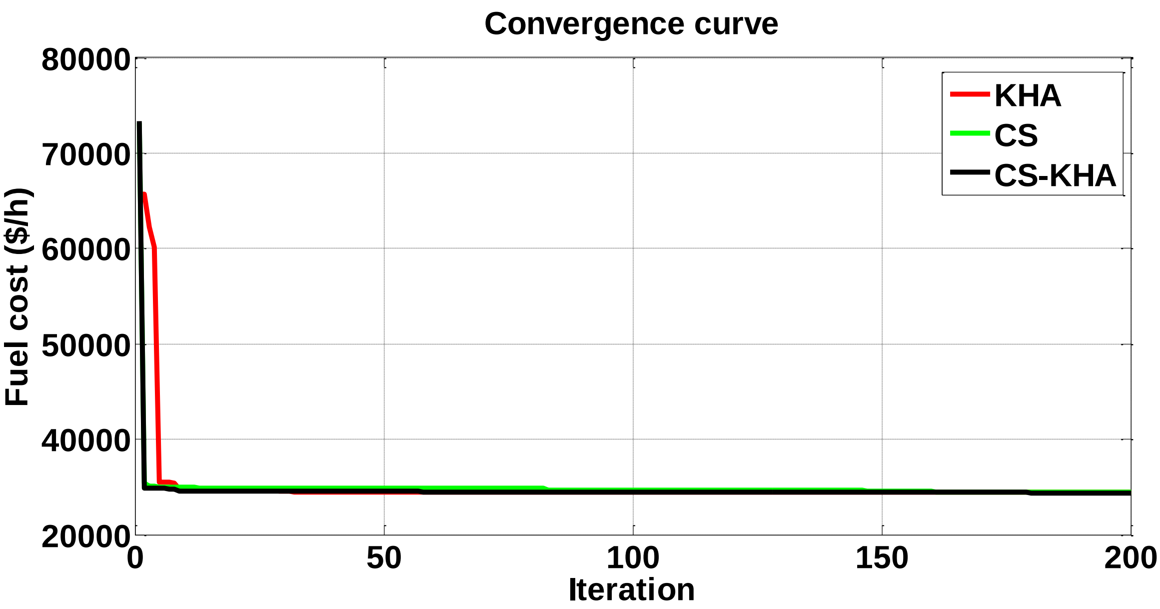

Figure 5.2. Convergence characteristics of case 2.

5.3.3 Test case 3a: 13 generators with 1800 MW

Case 3 comprises of thirteen generators that process the valve point effects for a load demand of 1800 MW. It is a great system with further non-linearity and the system data are given in [7]. The population size employed for simulation of KHA, CS and CSKHA is set to100, and the maximum iterations are 500 for whole techniques. The statistical outcome for the comparison of whole techniques exams are outlined in table 5, Compared to the results obtained by other techniques, the solutions yielded by CSKHA are clearly better. In this case any result of hybrid parallel CSKHA is better than hybrid series CSKHA or at least equal to it. Contrasting these results, we can observed that the technique suggested in this work can very well solve great power systems and surpass other techniques in terms of efficiency as well as the robustness of the method.

So as to notice the difference between these techniques, the comparison of a selected technique of the convergence curves of these illustrative methods is shown in Figure 3. It can be seen from Figure 3 that the CSKHA has clearly surpassed other techniques in terms of the quality of the solution.

Table 5.5. The optimal results get from the case 3a.

Control Variables	CSKHA	KHA	CS
P_1 (MW)	628,3185	628,3198	628,2930
P_2 (MW)	149,5995	224,3489	224,3904

P_3 *(MW)*	222,7503	148,0612	148,0304
P_4 *(MW)*	109,8665	60	109,8743
P_5 *(MW)*	109,8665	109,8649	60
P_6 *(MW)*	109,8665	109,8672	109,8489
P_7 *(MW)*	109,8665	109,8536	109,8646
P_8 *(MW)*	109,8658	109,8436	109,8405
P_9 *(MW)*	60	109,8409	109,8578
P_{10} *(MW)*	40	40	40
P_{11} *(MW)*	40	40	40
P_{12} *(MW)*	55	55	55
P_{13} *(MW)*	55	55	55
Fuel Cost *($/h)*	**17960.3696**	**17960,8259**	**17960,9107**

Table 5.6. Comparison of results for case 3a

methods	**Fuel Cost *($/h)***
CSKHA^1	**17960.3696**
KHA	**17960,8259**
CS	**17960,9107**
CSKHA^2	**17960.3703**
DE [8]	17963.83
PSO-SQP [9]	17969.93
FA [10]	17963.8308
OIWO [11]	17963.83
MABCA [12]	17963.83

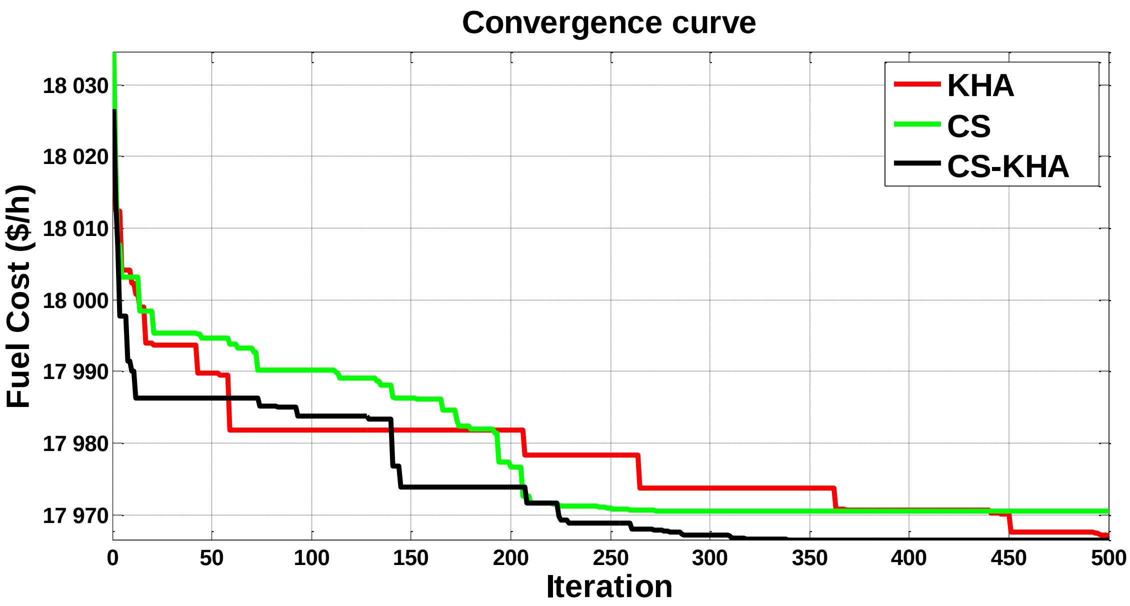

Figure.5.3.Convergence characteristics of case 3a.

5.3.4 Test case 3b: 13 generators with 2520 MW

For the other case of thirteen generating units with a load demand of 2520 MW, the comparative assessment among the preferable solution obtained by all variations of the CSKHA is given in table 7. The system data are given in [7]. The population size employed for simulation of KHA, CS and CSKHA is set to100, and the maximum iterations are 500 for whole techniques. The results yielded by the suggested hybrid parallel CSKHA variations for the second case are too compared with those recently reported of the state of the art techniques employed the same case of thirteen generating units with load demand of 2520 MW. Interestingly, the superior solutions are obtained by the suggested techniques in general. It is obvious that the hybrid parallel CSKHA technique outperforms hybrid series CSKHA. The survey of the update process under the hybrid parallel CSKHA is a significant area of research that deserves further consideration for the ELD domain, as given in table 8.

Table 5.7. The optimal results get from the case 3b.

Control Variables	CSKHA	KHA	CS
P_1 *(MW)*	628,9383	628,1279	628,38663
P_2 *(MW)*	449,7188	449,2578	450,47423
P_3 *(MW)*	299,1131	301,5702	300,51176
P_4 *(MW)*	160,0782	159,8100	159,64271
P_5 *(MW)*	110,5687	162,8327	160,71978
P_6 *(MW)*	160,2294	159,7543	158,96331

P_7 *(MW)*	160,6838	160,3695	109,91751
P_8 *(MW)*	162,1647	110,4224	161,3046
P_9 *(MW)*	159,4758	159,8721	160,3680
P_{10} *(MW)*	40	40	40
P_{11} *(MW)*	78,5156	77,2329	40,1863
P_{12} *(MW)*	55,0743	55,7496	57,4553
P_{13} *(MW)*	55,4386	55	92,0697
Fuel Cost *($/h)*	**24164,1265**	**24165,8502**	**24167,8007**

Table 5.8. Comparison of results for case 3b.

methods	**Fuel Cost ($ /h)**
CSKHA^1	**24164,1265**
KHA	**24165,8502**
CS	**24167,8007**
CSKHA^2	**24164,1267**
DE [8]	24169.92
PSO-SQP [9]	24261.05
MABCA [12]	24169.917

5.3.5 Test case 4: 40 generators

This case deliberates forty generators as an extensive power system to prove the excellence of CSKHA on other techniques to get an optimal solution. In addition, the valve point loading effect is considering to entire the test [13-15]. The data for this system is presented in [14]. Table 9 shows the outputs of every unit for a load demand of 10 500 MW and the cost of every technique. It can be remarked that the proposed hybrid parallel CSKHA obtains a lower cost than other methods while obtaining the generations' constraints. As a result, these techniques have been restricted in local minimum solutions. Consequently, hybrid parallel CSKHA results better than the hybrid series CSKHA and other methods in whence of fuel cost, even for an extensive power system with valve loading effect. In addition, table 10 presents the statistical comparison between hybrid parallel CSKHA, hybrid series CSKHA and various techniques. Obviously the fuel cost yielded by suggested hybrid parallel CSKHA is better than other techniques. Furthermore, a curve of the convergence rate of the objective function is presented in Fig. 4. It can be noticed that, the suggested CSKHA gives better convergence results than original KHA, CS.

Table 5.9. The optimal results get from the case 4.

Control Variables	CSKHA	KHA	CS
P_{1} (MW)	113,3826	113,9681	112,3255
P_{2} (MW)	111,2976	107,0362	112,8611
P_{3} (MW)	96,67379	106,2199	103,8149
P_{4} (MW)	162,8772	179,8851	163,5639
P_{5} (MW)	96,44311	95,6386	94,66628
P_{6} (MW)	132,9046	119,3762	129,6807
P_{7} (MW)	279,0002	294,0993	285,2763
P_{8} (MW)	293,6999	269,2463	276,4915
P_{9} (MW)	288,3165	299,3320	280,8487
P_{10} (MW)	216,8368	169,1547	192,4161
P_{11} (MW)	217,05268	205,6456	214,7706
P_{12} (MW)	220,08281	219,5819	224,7711
P_{13} (MW)	322,10773	310,9034	356,5067
P_{14} (MW)	335,75678	335,2200	325,02570
P_{15} (MW)	325,84418	363,2386	302,35299
P_{16} (MW)	328,76712	353,2160	360,87880
P_{17} (MW)	439,90933	441,00975	441,80349
P_{18} (MW)	455,67061	429,78433	424,78466
P_{19} (MW)	481,7095	489,09685	467,5932
P_{20} (MW)	479,4472	484,97340	471,0211
P_{21} (MW)	518,8881	515,51093	506,1676
P_{22} (MW)	497,9332	473,4612	488,8075
P_{23} (MW)	522,7407	516,6089	536,2016
P_{24} (MW)	515,8417	493,2262	515,8895
P_{25} (MW)	459,1075	506,2600	513,0993
P_{26} (MW)	473,7741	489,7204	531,2136
P_{27} (MW)	12,4575	19,35058	10,39765
P_{28} (MW)	10,0209	12,50855	11,68895
P_{29} (MW)	10,8877	13,75471	13,25302
P_{30} (MW)	96,12181	96,98621	96,99459
P_{31} (MW)	187,6265	187,3150	187,2937
P_{32} (MW)	189,5840	188,0885	189,2611
P_{33} (MW)	189,9985	189,9641	189,9859
P_{34} (MW)	198,7560	198,5638	195,4582
P_{35} (MW)	199,90909	199,9696	198,2204
P_{36} (MW)	196,19328	197,4649	199,9881

P_{37} *(MW)*	109,32398	108,2215	109,4987
P_{38} *(MW)*	107,36649	109,7875	100,3496
P_{39} *(MW)*	105,92094	108,18505	107,3261
P_{40} *(MW)*	499,76633	488,42431	457,4501
Fuel Cost *($ /h)*	**121411.4286**	**121411.6739**	**121413.8473**

Table 5.10. Comparison of results for case 4.

Methods	Fuel Cost *($ /h)*
CSKHA^1	**121411.4286**
KHA	**121411.6739**
CS	**121413.8473**
CSKHA^2	**121411.4289**
IWO[22]	121412.54
QPSO[23]	121424.6399
CBA[24]	121412.5468
FA[25]	121415.05
HGA[26]	121602.81

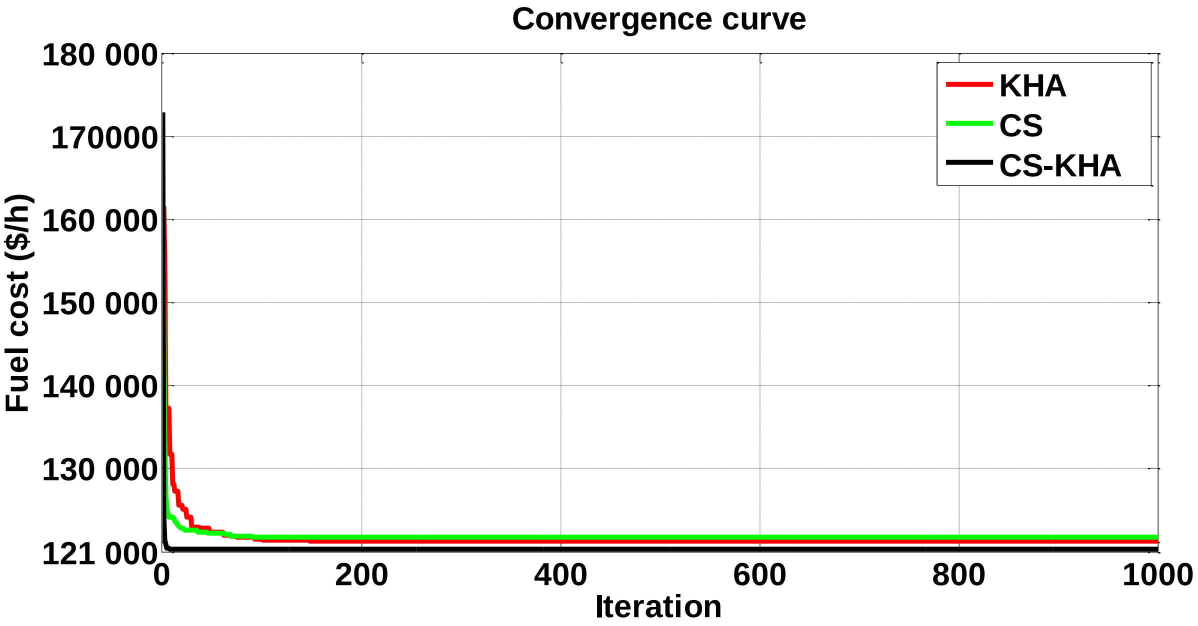

Figure 5.4. Convergence characteristics of case 4.

5.3.6 Combined economic emission dispatch

The atmospheric contaminants like sulfur oxides, nitrogen oxides and carbon dioxide generated by fossil fuel fired generator can be modeled separately [16,17]. Nevertheless, For comparison goals, the total emission of these contaminants, which is the sum of a quadratic and exponential function, can be formulated, the optimization cost of production have been expressed from the conventional ELD with emission and of line flow constraints.

The CEED surveys are deliberated to search for the simultaneous minimization of two functions defined by the same variable objects obtaining a double objective optimization problem or bi-criteria. The primary hardness with such an optimization problem is related with the existence of conflicts between two structures. For which, we have transformed this problem into a single-objective optimization problem.

5.3.7 Test Case 5 generators: Environmental dispatch

In this case, our objective function, thus we only optimize NO_X emissions, and the results are shown in table 11 shows that, in the case of environmental dispatch, the rising in the load results in a rise in the NO_X emission rate. Despite the load variation, these three techniques satisfy the inequality constraint.

We too notice that the three meta-heuristics gave the same NO_X emission rate even though we rise the load, but CS is still the slowest and CSKHA converges quicker.

At preferable, the minimum production costs were determined by CS, KHA and CSKHA. Thus, for other power demand, it was CSKHA who gave the minimum production cost.

Therefore, in the case of the environmental dispatch of the 6-units system, hybrid parallel CSKHA gave the preferable result, quick and accurate and superior performance on the CSKHA hybrid series, and better than other techniques.

Table 5.11. The optimal results get from the case 5.

P_D =700 *(MW)*				P_D =800 *(MW)*		
Control Variables	CSKHA	KHA	CS	CSKHA	KHA	CS
P_1 *(MW)*	80,1458	80,1457	80,1459	100,5249	100,525	100,5247
P_2 *(MW)*	82,4038	82,4041	82,4043	103,7565	103,7569	103,7575
P_3 *(MW)*	113,965	113,9649	113,9645	127,0082	127,0083	127,009
P_4 *(MW)*	113,4753	113,4752	113,4746	126,3494	126,3491	126,3477
P_5 *(MW)*	163,4515	163,4516	163,4523	182,2065	182,2063	182,2052
P_6 *(MW)*	163,0983	163,0983	163,0982	181,7376	181,7376	181,7391
Ploss (MW)	16,5398	16,5397	16,5398	21,5832	21,5831	21,5831
Fuel Cost ($ /h)	38101,0062	38101,0081	38101,0132	43719,0251	43719,0353	43719,0418
Emission (t/h)	434,1306	434,1306	434,1306	548,7062	548,7062	548,7063

P_D =900 *(MW)*				P_D =1000 *(MW)*		
Control Variables	CSKHA	KHA	CS	CSKHA	KHA	CS
P_1 *(MW)*	120,9382	120,9383	120,9388	125	125	125
P_2 *(MW)*	125,3281	125,328	125,3303	149,9858	150	149,9999
P_3 *(MW)*	140,1958	140,1957	140,1954	156,4114	156,2957	156,4904
P_4 *(MW)*	139,3406	139,3406	139,3399	154,9218	155,313	155,1614
P_5 *(MW)*	201,0838	201,084	201,0824	224,3073	224,2136	223,4913
P_6 *(MW)*	200,4819	200,4818	200,4816	223,1039	222,9043	223,5844
Ploss (MW)	27,3685	27,3685	27,3684	33,7302	33,7266	33,7274
Fuel Cost *($ /h)*	49650,2228	49650,223	49650,2955	55455,6022	55456,7748	55457,2911
Emission (t/h)	682,6256	682,6258	682,6260	837,7686	837,7683	837,7699

Table 5.12. Comparison of results for case 5.

PD(MW)	Methods	CSKHA[1]	KHA	CS	CSKHA[2]	FA [4]	BA [4]	FA-BA [4]
700	Cost *($ /h)*	38101,0062	38101,0081	38101,0132	38101,0064	38101.09	38100.95	38101.13
	Emission*(t/h)*	434,1306	434,1306	434,1306	434,1307	434.13	434.13	434.13
	Ploss (MW)	16,5398	16,5397	16,5398	16,5399	16.5398	16.5397	16.5397
800	Cost *($ /h)*	43719,0251	43719,0353	43719,0418	43719,0253	43719.20	43719.15	43716.14
	Emission*(t/h)*	548,7062	548,7062	548,7063	548,7063	548.70	548.70	548.70
	Ploss(MW)	21,5832	21,5831	21,5831	21,5835	21.5833	21.5831	21.5830
900	Cost *($ /h)*	49650,2228	49650,223	49650,2955	49650,2229	49650.29	49650.14	49649.97
	Emission*(t/h)*	682,6256	682,6258	682,6260	682,6258	682.62	682.62	682.62
	Ploss(MW)	27,3685	27,3685	27,3684	27,3687	27.3684	27.3682	27.3685
1000	Cost *($ /h)*	55455,6022	55456,7748	55457,2911	55455,6023	55456.64	55456.49	55456.24
	Emission*(t/h)*	837,7686	837,7683	837,7699	837,7687	837.77	837.77	837.77
	Ploss(MW)	33,7302	33,7266	33,7274	33,7304	33.7301	33.7306	33.7337

5.3.8 Test Case 6 generators the combined economic environmental dispatch

The next table presented the results of the record (see table 13): Even in the case of CEED, the whole three techniques respected the inequality constraint for various loads.

We notice that the augment in the load too results in the augment of the total cost. It too appear that the three techniques gave the same total cost and that, despite the changes in demand and in the respect of constraint of equality. The difference among the three meta-heuristics was the simulation time when CSKHA was the quick of the offered optimum.

Table 14 can summarize the comparison between seven methods and the best one with the proposed hybrid parallel CSKHA method. With the best combined cost with emission values of 57188.8460 $/hr. This table denotes that the hybrid parallel CSKHA method acquires the lowest value of fuel cost and emission related to two updated methods. The proposed hybrid parallel

CSKHA method can give the lowest values for combined cost and emission better than hybrid series CSKHA and other techniques as shown through table 14.

Table 5.13. The optimal results get from the case 6.

P_D =700 *(MW)*				P_D =800 *(MW)*		
Control Variables	CSKHA	KHA	CS	CSKHA	KHA	CS
P_1 *(MW)*	62,096683	62,10440	62,10446	76,5721673	76,57218	76,57261
P_2 *(MW)*	61,663009	61,6733	61,67324	79,260657	79,26060	79,26108
P_3 *(MW)*	119,97424	119,97	119,9717	135,23063	135,230	135,2305
P_4 *(MW)*	119,47485	119,4722	119,47239	134,15267	134,1527	134,15255
P_5 *(MW)*	178,20113	178,19381	178,19374	199,70981	199,7096	199,70939
P_6 *(MW)*	175,64687	175,64088	175,6409	197,26306	197,26317	197,26284
Ploss (MW)	17.056799	17.0564	17.0564	22.1890	22.1890	22.18899
Emission (t/h)	439.6125	439.6074	439.6074	557.2014	557.2014	557.2011
Fuel Cost *($ /h)*	37500.6665	37500.8975	37500.8967	42784.3583	42784.35814	42784.3722
combined	57188.8460	57189.99043	57190.3439	67739.62947	67739.7966	67740.2981

P_D =900 *(MW)*				P_D =1000 *(MW)*		
Control Variables	CSKHA	KHA	CS	CSKHA	KHA	CS
P_1 *(MW)*	92,329613	92,32966	92,3297	107,163088	107,16313	107,163196
P_2 *(MW)*	98,391242	98,39113	98,391260	116,550320	116,5505	116,550507
P_3 *(MW)*	150,19466	150,1947	150,19480	165,661886	165,6618	165,661817
P_4 *(MW)*	148,55918	148,5590	148,55899	163,402481	163,40257	163,402526
P_5 *(MW)*	220,40443	220,40433	220,40426	242,03117	242,03117	242,031069
P_6 *(MW)*	218,13053	218,130719	218,130601	239,802232	239,80186	239,802056
Ploss (MW)	28.00967	28.00967	28.0096	34.61118	34.6111	34.611
Emission (t/h)	693.78786	693.78788	693.78780	851.5334	851.5333	851.5333
Fuel Cost *($ /h)*	48350.6553	48350.6543	48350.6583	54124.1825	54124.1897	54124.1892
combined	81528.9092	81528.9786	81529.1173	94846.1317	94846.21687	94846.38718

Table 5.14. Comparison of results for case 6.

PD (MW)	methods	CSKHA^1	KHA	CS	CSKHA^2	FA [4]	BA [4]	FA-BA [4]
700	Combined	57188.8460	57189.9904	57190.3439	57188.8461	57190.01	57190.01	57190.01
	Fuel cost*($/h)*	37500.6665	37500.8975	37500.8967	37500.6667	37500.93	37500.84	37500.48
	Emission (t/h)	439.6125	439.6074	439.6074	439.6126	439.61	439.61	439.62
	Ploss (MW)	17.056799	17.0564	17.0564	17.056799	17.0566	17.0566	17.0569
800	Combined	67739.6294	67739.7966	67740.2981	67739.6296	67740.26	67740.26	67740.26
	Fuel cost*($/h)*	42784.3583	42784.3581	42784.3722	42784.3584	42784.41	42784.52	42784.36
	Emission (t/h)	557.2014	557.2014	557.2011	557.2017	557.20	557.20	557.20
	Ploss (MW)	22.1890	22.1890	22.18899	22.1892	22.1890	22.1888	22.1888
900	Combined	81528.9092	81528.9786	81529.1173	81528.9094	81529.09	81529.09	81529.09
	Fuel cost*($/h)*	48350.6553	48350.6543	48350.6583	48350.6556	48350.59	48350.77	48350.54
	Emission (t/h)	693.78786	693.78788	693.78780	693.78787	693.79	693.78	693.79
	Ploss (MW)	28.00967	28.00967	28.0096	28.00969	28.0098	28.0094	28.0095
10^3	Combined	94846.1317	94846.2168	94846.3871	94846.1318	94846.36	94846.36	94846.36

	Fuel cost*($/h)*	54124.1825	54124.1897	54124.1892	54124.1826	54124.28	54124.12	54124.13
	Emission (t/h)	851.5334	851.5333	851.5333	851.5335	851.53	851.53	851.53
	Ploss (MW)	34.61118	34.6111	34.611	34.61119	34.6112	34.6113	34.6113

5.3.9 Test Case 7: 10 generators

In this case, a 10-unit generating thermal system taking into account valve point effect is studied. Fuel cost factor; generator constraints, emission coefficients and transmission loss coefficient matrix are presented in [18]. Table 15 provides an overview of the results of using the CSKHA to solving the CEED to 2000MW load demand and compares with other techniques [18-21].

The result of the proposed technique is highlighted here. The proposed hybrid parallel CSKHA obtain a lower cost than that of hybrid series CSKHA, CSABC_PSO, GSA, EMOCA, MODE and PDE respectively system constraints. Moreover, its emission is too less than ABC_PSO, GSA, EMOCA, MODE and PDE. As a result, hybrid parallel CSKHA has successfully implemented a global minimization solution. In addition, the calculation time is shorter than the other technique. Therefore, hybrid parallel CSKHA is superior on other techniques in reducing net costs in the shortest possible time. Hence, the convergence of costs for this application is shown in Fig. 5.5.

Table 5.15. The optimal results get from the case 7.

Control Variables	CSKHA	KHA	CS
P_1 *(MW)*	54,9999	54,9998	54,9999
P_2 *(MW)*	79,9579	72,0709	71,94645
P_3 *(MW)*	80,2342	91,5071	96,90161
P_4 *(MW)*	84,7818	87,6035	82,53404
P_5 *(MW)*	159,9999	159,999	144,0075
P_6 *(MW)*	199,5256	198,4461	198,6948
P_7 *(MW)*	288,0045	293,4512	291,9204
P_8 *(MW)*	294,2520	305,62483	306,8564
P_9 *(MW)*	414,9251	407,73395	419,9366
P_{10} *(MW)*	426,15949	410,86248	414,9691
Fuel Cost *($/h)*	**113369.53734**	**113383.3562**	**113381.6452**
Emission *(t/h)*	**4000.86999**	**4005.916905**	**4047.3204**
Ploss (MW)	**83.84078**	**83.29999**	**83.767188**

Table 5.16. Comparison of results for case 7.

Method	**Fuel Cost *($/h***	**Emission *(t/h)***	***Ploss (MW)***
CSKHA[1]	**113369.53734**	**4000.86999**	**83.84078**
KHA	**113383.3562**	**4005.916905**	**83.29999**
CS	**113381.6452**	**4047.3204**	**83.767188**
CSKHA[2]	**113369.53735**	**4000.87000**	**83.84079**
MODE[18]	113484	4124.9	84.33
NSGAII [18]	113539	4130.2	84.25
PDE [18]	1.1351	4111.4	83.9
GSA [19]	1.1349	4111.4	83.9869
ABC_PSO [20]	1.1342	4120.1	84.1736
EMOCA [21]	1.13445	4113.98	83.56

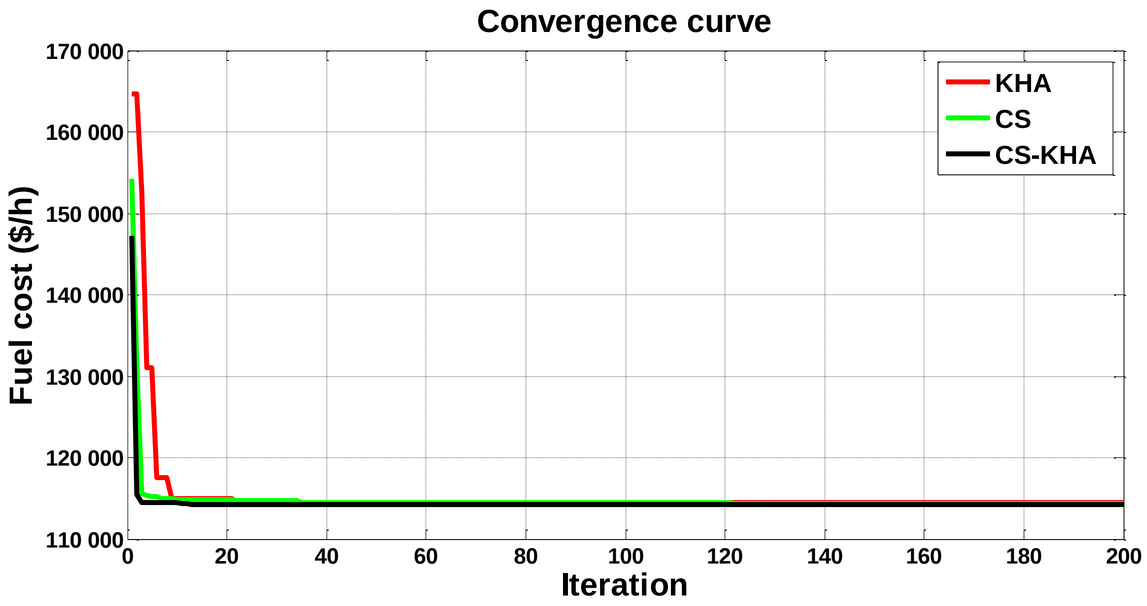

Figure.5.5. Convergence characteristics of case 7.

5.3.10 Test Case 8: 40 generators (CEED)

This exam system is composed of 40 generators with non-smooth fuel cost and emission functions. The coefficients of this unit are given in [18]. Table 17 outlines the results of the solving of CEED for a 10500 MW load demand applied hybrid parallel CSKHA and the preferable emissions and preferable compromising cost get using this technique is **191555.5116** $/h, respectively. It must be noted that the total cost of a compromise solution is specified by the price penalty factor, as confirmed by the procedure reported in [5]. The best compromise cost achieved by hybrid parallel CSKHA reflects a fuel cost of 128715.9474$/hour and an emission level of 178527.7143 ton/h. The result of the proposed hybrid parallel CSKHA technique gives a lower fuel cost than the hybrid series CSKHA and others as appear in table 18. As a result, these techniques have been trapped in local minimum solutions.

Table 5.17. The optimal results get from the case 8.

Control Variables	CSKHA	KHA	CS
P_1 (MW)	36	36	36
P_2 (MW)	114	113,9999	113,2143
P_3 (MW)	119,9999	119,9997	104,4055
P_4 (MW)	176,8302	175,6958	142,6987
P_5 (MW)	97	74,2514	90,52909
P_6 (MW)	124,8071	126,5859	121,0474
P_7 (MW)	300	299,9999	287,7625
P_8 (MW)	293,1287	292,6840	284,60975
P_9 (MW)	291,60683	290,9985	284,6498
P_{10} (MW)	130	130,0021	130
P_{11} (MW)	303,5538	303,8570	289,6774
P_{12} (MW)	302,1455	303,8355	288,2398
P_{13} (MW)	419,4725	412,6947	394,29904
P_{14} (MW)	395,0146	394,8488	394,27941
P_{15} (MW)	396,0751	397,0887	394,27936
P_{16} (MW)	395,1527	396,7668	394,27938
P_{17} (MW)	441,8800	443,7352	411,72796
P_{18} (MW)	443,9516	444,8504	423,22094
P_{19} (MW)	428,9352	429,4401	421,51961
P_{20} (MW)	427,0561	429,6222	421,52206
P_{21} (MW)	433,5302	433,5196	433,52002
P_{22} (MW)	433,5309	433,52461	433,51941
P_{23} (MW)	433,5220	433,53456	433,51946
P_{24} (MW)	433,5389	433,52179	433,51953
P_{25} (MW)	433,5397	433,542836	433,51959
P_{26} (MW)	433,6004	434,025573	433,51961
P_{27} (MW)	17,1541	17,9352113	14,136707
P_{28} (MW)	17,4017	17,0704870	13,464591
P_{29} (MW)	16,4817	19,3720561	11,513262
P_{30} (MW)	96,2552	97	88,498813
P_{31} (MW)	173,2095	175,7677	167,2802
P_{32} (MW)	172,8961	171,1173	166,8738

P_{33} *(MW)*	172,7233	173,0552	167,1975
P_{34} *(MW)*	199,9999	200	199,9999
P_{35} *(MW)*	199,9999	200	199,9999
P_{36} *(MW)*	200	200	200
P_{37} *(MW)*	102,6710	101,8404	91,73487
P_{38} *(MW)*	96,92331	96,62931	96,32926
P_{39} *(MW)*	103,6140	101,3076	100,7977
P_{40} *(MW)*	429,8350	426,1325	421,5913
Fuel Cost *($ /h)*	**128715.9474**	**128721.2767**	**128734.8931**
Emission*(t/h)*	**178527.7143**	**178535.7403**	**178539.6783**
F total	**191555.5116**	**191556.8550**	**191559.5888**

Table 5.18. Comparison of results for case 8.

Method	**Fuel Cost** *($ /h)*	**Emission***(t/h)*	Combined
CSKHA^1	**128715.9474**	**178527.7143**	**191555.5116**
KHA	**128721.2767**	**178535.7403**	**191556.8550**
CS	**128734.8931**	**178539.6783**	**191559.5888**
CSKHA^2	**128715.9475**	**178527.7145**	**191555.5118**
DE-HS [22]	128713.8868	178634.0971	191589.5164
DE[22]	NA	NA	191594.5053
MBFA [23]	NA	NA	190,591.1967
CKH [24]	128717.4718	178529.9616	191556.4494

5.4 Conclusion

In this chapter, we have offered a new technique resulting from the hybridization of two current meta-heuristics inspired by nature: KHA and CS. They were hybridized in two ways, first on the hybrid parallel and the other on the hybrid series, We have developed this new method so as to solve the ELD and CEED problems for various power systems and load demands.

First, we have used our three techniques on a simple five-node network with three generators to guarantee their efficiency compared to the other methods and the result was very successful. Thus, we exam the 6, 10, 13 and 40 units. The results found by the suggested technique are compared with different other optimization methods. The comparison assures the superiority of hybrid parallel CSKHA over the hybrid series CSKHA and other techniques for settling ELD and CEED problems until for large scale power system with considering valve point effect. The obtained results showed that hybridization integrates the advantages of KHA and CS. Thus it gives us a decrease of cost of production and toxic gas emission rates whole with quickly convergence and within the imposed constraints.

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General conclusions

Deregulation of Power systems needs increased attention in terms of safety. In the vertical structure, since the production, transport and distribution companies belong to a single entity, the safety, monitoring and control of the power system are easy. But these are difficult to achieve in the context of deregulation environment. In order to maintain the system in a safe state during emergency response, the monetary value needs to be considered. This cost is involved in this study as a security cost. Consumers connected to the system must benefit from this. Therefore, the consumer benefit is involved in the overall objective function. The cost of transmission must recover the fixed cost.

The work of this thesis involves the problem of optimal power flow (OPF). The OPF problem is formulated as the decrease of fuel costs, while limiting the active power generation boundaries and voltage security constraints. In the study of this thesis, four kinds of hybrid optimization techniques are used to solve the optimal power flow problem. These techniques such as hybrid parallel CSKHA and hybrid series CSKHA.

Optimization of every of the above mentioned technique is studied in depth, and every technique is adjusted appropriately to meet the requirements of OPF. The different parameters of each technique are carefully selecting a faster convergence. The dedicated calculator programs were developed in MATLAB for OPF solutions.

The work of this thesis has obtained extensive simulation results, which correspond to three typical cases of IEEE 30, IEEE 57 and 118 bus systems. Various performance pointers for OPF problems, namely fuel cost and voltage profile, are calculated and studied. Different characteristic tables and curves are plotted to evaluate and explain the performance of the suggested techniques. The results show that the hybrid techniques show good effectiveness. It can thus be concluded that these approaches are promising applicants for the OPF problem.

The another suggested research study introduce effective technique, namely hybrid parallel CSKHA and hybrid series CSKHA to solve the problems of economic dispatch and combined economic emission dispatch. This approach has their own advantage and abilities while solving the different problems associated with the economic dispatch and combined economic emission dispatch.

Different applications networks such as 3, 6, 10, 13 and 40 generators and case studies have been suggested to demonstrate the applicability of these suggested optimization techniques to solve the problem of power economic dispatch and combined economic emission dispatch.

Future work

Summarizes the results of this suggested study and outlines appropriate recommendations for future research work in the context of the topic purview.

- Different settings of optimization techniques used in this thesis are chosen by trial and error to improve convergence characteristics. In the future, these settings can too be optimized for improved effectiveness.

-In the future, different FACTS devices can be incorporated into the power system networks and the effectiveness of different FACTS devices aiming to minimize production cost can be studied.

- Various types of sources energy, like solar cells, wind turbines, micro-turbines and fuel cells, can be involved in solving OPF problems.