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Adaptive Gaining-Sharing Knowledge Based Algorithm for Economic Dispatch Considering Valve-Point Effect and Multi Fuel Options

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Dedication Necib Islam

I dedicate this work to the people closest to my heart thoses who help me throw this all years whose been encourage me , provide knowledge and teaching and getting erudition and learning starting with

First of all : my father ABDELATIF May God have mercy on him, My mother the one and only who push me and been always there for me for all time may god save Her and I appreciate everything you did and you still doing it May God bless you and keep you safe, My Brothers Chawki, Fahed, Fares ,Iskander,My Sisters the two lovely ones Jihane and Zahra, my friends Prom of Electrical Network Second Year Class 2023, my Supervisor Larouci Benyekhlef May God Bless you thank your for all the effort and sharing of information to make this thesis done and set properly.

Dedication Mustapha Aoudjit

I dedicate this work to those closest to my heart who have encouraged me, provided information and education, and helped me gain erudition and learning through the years, beginning with

My mother: I would want to express my heartfelt appreciation to you for the love and support you have shown me and my family. May God bless you and keep you safe, first and foremost, my father Khelifa, I would want to express my gratitude and gratitude for the encouragement you have provided; may God bless you, My Grand Mother Yay Wiza, My Sisters Sofia, Ritad, Lina, My Friends Electrical Network Second Year Class Prom 2023,My Supervisor, Larouci Benyekhlef I pray that God rewards you generously for the time and effort you put into writing and sharing in this thesis.

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Abstract

Economic dispatch (ED) is a crucial component of every power system. Lambda-Iterative, Newton-Raphson, quadratic programming (QP), etc., are the conventional techniques for solving ED. However, non-quadratic functions cannot be solved by conventional methods, the input-output characteristics of a generator are significantly non-linear, which poses a challenging non-convex and non-smooth optimization problem which is non quadratic input functions for economic dispatch, In this study, the adaptive gain-sharing knowledge algorithm has been applied and implemented to function and solve the electrical dispatch for multi-systems and variation of unit numbers to solve power demand with the lowest possible cost of fuel and even emission, the AGSK optimization is updated from the original GSK (gaining and sharing knowledge) to solve the non-convex problem and be able to resolve it. The presented algorithm (AGSK) showed superior performance in terms of The total cost of power generated has been the lowest considering variables such as transmission losses, VPE, MFO, and system emission compared with the other four state-of-the-art algorithms.

Keywords

Economic dispatch. Quadratic Programming, Valve Point Effects, Multi Fuel Option, Emission, Adaptive Gain-Sharing Knowledge (AGSK), Cost Of Fuel, Transmission Losses.

Résumé

Le Dispatching économique (ED) est une composante cruciale de tout système électrique. Lambda-Iterative, Newton-Raphson, la programmation quadratique (QP), etc., sont les techniques conventionnelles pour résoudre ED. Cependant, les fonctions non quadratiques ne peuvent pas être résolues par les méthodes conventionnelles, les caractéristiques d'entrée-sortie d'un générateur sont significativement non linéaires, ce qui pose un problème d'optimisation non convexe et non lisse qui sont des fonctions d'entrée non quadratiques pour la répartition économique. Dans cet mémoire, l'algorithme "adaptive gain-sharing knowledge"a été appliqué et mis en œuvre pour fonctionner et résoudre la répartition électrique pour les multi-systèmes et la variation des nombres d'unités pour résoudre la demande d'énergie avec le coût le plus bas possible du carburant et même des émissions, l'optimisation AGSK est mise à jour à partir du GSK original (gain et partage des connaissances) pour résoudre le problème non convexe et être en mesure de le résoud L'algorithme présenté (AGSK) a montré des performances supérieures en termes du. Le coût total de l'énergie générée a été une des variables les plus faibles en considération telles que les pertes de transmission, Effets de points de valves, Options Multi-Combustibles, et les émissions du système par rapport aux autres algorithmes.

Mots clés

Dispatching économique. programmation quadratique , , Effets de points de valves, Options Multi-Combustibles, Émissions, Adaptive Gain-Sharing Knowledge (AGSK), Le coût total, les pertes de transmission.

الملخص

التوزيع الكهربائي (ED) هو عنصر حاسم في أي نظام كهربائي. Lambda-Iterative، Newton-Raphson، البرمجة التربيعية (QP)، إلخ، هي التقنيات التقليدية لحل ED. ومع ذلك، لا يمكن حل الوظائف غير التربيعية بالطرق التقليدية، وخصائص المدخلات والخرج للمولد غير خطية بشكل كبير، مما يطرح مشكلة التحسين غير المحدب وغير السلس والتي هي وظائف مدخلات غير تربيعية للتوزيع. في هذه المذكرة، تم تطبيق الخوارزمية «معرفة مشاركة الكسب التكيفية» وتنفيذها لتشغيل وحل التوزيع الكهربائي للأنظمة المتعددة والاختلاف في عدد الوحدات لحل الطلب على الطاقة بأقل تكلفة ممكنة للوقود وحتى الانبعاثات، يتم تحديث AGSK من GSK الأصلي (اكتساب المعرفة وتبادلها) لحل المشكلة غير المحدب تم تطبيق وتنفيذ "خوارزمية" معرفة تقاسم المكاسب التكيفية "لتشغيل وحل التوزيع الكهربائي للأنظمة المتعددة وتغيير عدد الوحدات لحل الطلب على الطاقة بأقل تكلفة ممكنة للوقود وحتى الانبعاثات، ويتم تحديث تحسين AGSK من GSK الأصلي (اكتساب المعرفة وتقاسمها) لحل المشكلة غير المحدبة والقدرة على حلها. كانت التكلفة الإجمالية للطاقة المولدة واحدة من أقل المتغيرات في الاعتبار مثل خسائر النقل وتأثيرات نقاط الصمام وخيارات الوقود المتعدد وانبعاثات النظام مقارنة بالخوارزميات الأخرى.

الكلمات المفتاحية

التوزيع الكهربائي. البرمجة التربيعية،، تأثيرات نقاط الصمام، خيارات الوقود المتعدد، الانبعاثات، معرفة تقاسم المكاسب التكيفية (AGSK)، التكلفة الإجمالية، خسائر النقل.

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Acronyms

ELD	Economic Load Dispatch
PELD	Power Economic Load Dispatch
ECD	Emission Constrained Dispatch
EED	Economic And Emission Dispatch
GSK	Gaining sharing knowledge
AGSK	Adaptive Gaining sharing knowledge
MFO	Multi-Fuel Options
VPE	Valve Point Effects
VPL	Valve Point Load
POZ	Prohibited Operating Zone
PSO	Particle Swarm Optimization
DE	Differential Evolution
SA	Simulated Annealing
KHA	Krill Herd Algorithm
ACO	Artificial Bee Colony
Kf	Knowledge Factor
Kr	Knowledge Ratio
TLBO	Teaching Learning-Based Optimization
CEED	Combined Economic Emission Dispatch
FC	Fuel Cost
TC	Total Cost
EPSO	Enhanced Particle Swarm Optimization

General Introduction

In today's rapidly evolving Energy landscape, effective management of electrical dispatching is becoming increasingly important, Electrical dispatching involves the real-time optimization of power generation and distribution to meet changing energy demands while maintaining grid stability, To achieve this goal, it is necessary to have a comprehensive understanding of the complex interactions between various components of the electrical system, including generation sources, transmission lines, and distribution on the industry, Dispatchers are responsible for ensuring that the electricity grid operates smoothly and efficiently, and they must be able to react swiftly to fluctuations in demand or supply, Electric dispatching involves dispatching each generator based on its individual characteristics and performance, taking into account all previous equations noted in chapters such as fuel cost, valve point effect and even emision in order to arrive at the optimal solution, this limitation is surmounted by the AGSK algorithm, which allows generators to share their knowledge and experience, This algorithm employs machine learning and artificial intelligence techniques to analyze data from various generators and identify patterns and trends in their behavior, as well as the optimal procedure they can attempt on the power grid, As generators exchange knowledge and experience, the algorithm adapts and modifies its dispatch decisions to increase the grid's overall efficiency, This enables generators to minimizing waste and minimizing the risk of blackouts and enhancing the power grid's efficiency and sustainability, By optimizing the use of available resources, for new infrastructure and the environmental impact of power generation by taking into account emissions produced by the same generators at power generation centers, Overall, AGSK is a thrilling advancement in the potential to revolutionize the way we manage and operate power grids best results in terms of power quality, production cost, and environmental impact.

Chapter I

Economic Emission Dispatch Considering Valve-Point Effect and Multi-Fuel Option

Introduction:

The cost of producing energy, primarily in fossil fuel plants, is generally high due to the daily development in electricity consumption To minimize cost of fuel and sustain the steady functioning of the electrical grid, it has become increasing essential that we distribute the electricity economically, Energy must be distributed economically to save fuel costs and ensure the power network performs properly., The need to conduct production in the most cost-effective and efficient manner is also driven by the progressively increasing costs of coal, salaries, and other supplies[1].

Since certain installed generator-turbine units are more economical over others, those who should contribute more to the electricity generated, Also because of the non - linear nature of the cost curves, load distribution is not simple, Power Economic Load dispatch (PELD) tries to allocate a part of total load on each generator to optimally minimize the overall cost of operation, while meeting all the constraints[2] Thus, PELD is formulated as a problem of allocating generation among committed unit such that the total generation cost can be minimized satisfying all inequality and equality constraints. The basic equality constraint is that total output power of generating units must be equal to total demand and losses in the power system, Losses can be found by using Kron's formula, load flow analysis. Inequality constraints in economic load dispatch problem are ramp rate constraint valve point effect (VLP) , multifuel options (MFO) & prohibited operating zone (POZ)[3], security constraints, emission constraint etc, the committed power of each generator unit must be within prescribed limits.

I.1 Economic Load Dispatch problem

Economic Load Dispatch (ELD) is a key issue in the management and operation of the power system. Determining the best probable power generation schedule that matches the power units' generating limitations while using the lowest possible quantity of fuel is the aim of ELD [3]. The fuel expenses of power units are represented as quadratic functions in the canonical formulation of ELD. Quadratic functions are convex and are simple to solve using mathematical programming techniques. In the past few decades, a variety of conventional strategies have been utilized for dealing with ELD.

power system operating constraints, in- clouding power unit and load balancing constraints. the formulation described in the problem is formulated on one-hour time spans.

I.1.1. Objective function

The objective function of ELD [3] is defined as follows:

$$\sum_{i=1}^{n} F_i^c\,(P_i) \qquad (1)$$

where n is the total number of power units, $F_i^c\,(P_i)$ is the fuel cost function, for the i power units, and P_i is the power generation, for the i the power units according to the power generation schedule.

I.2. Economic and Emission Dispatches

I.2.1. Economic Dispatch

The proposed approach can accommodate non-quadratic (higher order) fuel cost and multiple emissions of differentiable nature objective function, The classical economic dispatch problem of finding the optimal combination of power generation, Which minimizes the total fuel cost while satisfying the total demand [5], Can be mathematically stated as follows:

$$F_T = \sum_{i=1}^{n} (a_i P_{Gi}^2 + b_i P_{Gi} + c_i) \quad \frac{\$}{h} \qquad (2)$$

(F_T): Total fuel cost (\$/h) (P_{Gi}): Generation of unit In (MW)

(a_i , b_i, c_i): Fuel Cost Coefficients Of Unit

(i ,n): Number Of Generating Unit

The economic dispatch problem is optimized by Serval Elements

I.2.1.1. Power balance constraint

The total power generated must supply total load demand and transmission losses [6].

$$\sum_{i=1}^{n} P_{Gi} = P_D + P_L \quad MW \qquad (3)$$

P_D: total load demand (MW) and P_L: total transmission losses (MW)

I.2.1.2. Transmission constraints

The transmission Power Losses (P_{Loss}) can be computed through a power flow computation (DC or AC approach), However, a common solve is to estimate the total transmission losses as a quadratic function of the power output of generating units in order to increase the clarity and splitting of the problem (known as Kron's loss formula) or through a simplified linear formula [3]

$$P_L = \sum_{i=1}^{n} \sum_{i=1}^{n} P_i B_{ij} P_j + \sum_{i=1}^{n} B_{0i} P_i + B_{00} \quad (4)$$

I-2-1-3 Unit capacity constraint

Each generator's power output, P_{Gi}, is limited to the range between its minimum and maximum values [3].

$$P_{Gi\ Min} \leq P_{Gi} \leq P_{Gi\ Max} \qquad (5)$$

$P_{Gi\ Min}$: minimum generation limit (MW)

$P_{Gi\ Max}$: maximum generation limit (MW)

I-2-1-4 Ramp rate limits:

Due to each unit's physical constraints, changing the output production of each unit is limited to a certain amount of power over a certain period of time, the generator ramp rate limits change the effective real power operating limits [5] as follows:

$$Max(P_i^{Min}, P_i(t-1) - DR \leq P_i(t) \qquad (6)$$

$$P_i \leq (Min(P_i^{Max}, P_i(t-1) + UR_I)$$

Where $P_i(t-1)$ is the output power of generator in the previous dispatch.

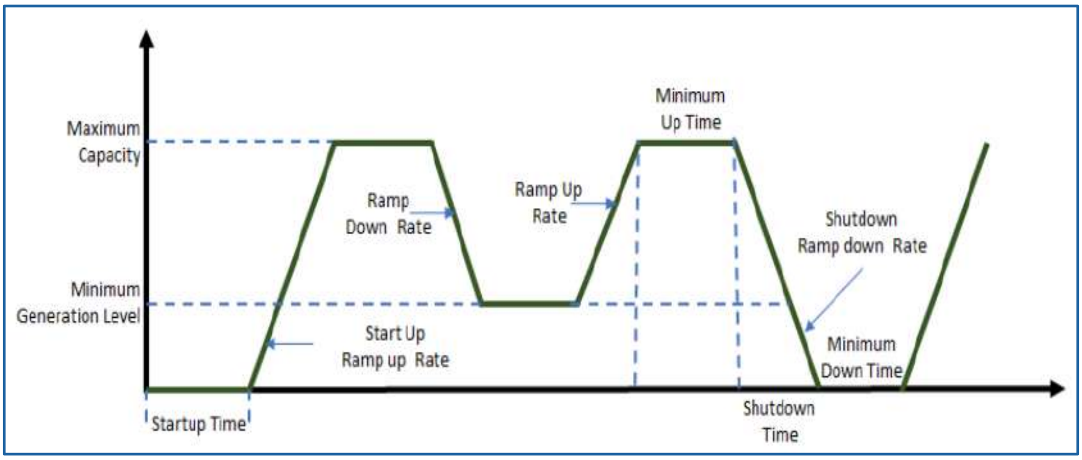

Figure 1: flexibility attributes of generators.

I.2.1.5 Prohibited Operating Zone (POZ)

The operating range of all generating units is practically restricted by their ramp rate limits to operate continually between the two closest specific operating zones

$$P_i^{Min} \leq P_i \leq P_{i,1}^{Low} : P_{i,k-1}^{Up} \leq P_i \leq P_{i,k}^{Low} : P_{i,ni}^{Up} \leq P_i \leq P_i^{max} \quad (7)$$

I.2.2. Emission Dispatches

The emission function can be expressed as the sum of all types of emission [7] considered, such as NOx, SO2, CO2, particles thermal emissions, with appropriate weighting of prices for each pollutant released A variety of mathematical representations of the Thermal generating systems emission function.

The following emission function (8) will be taken into aspect in this study to model the total emission levels of all producing units.

$$\boxed{E_i(P_{G_i}) = \sum_{i=1}^{n} (\alpha_i P_{Gi}^2 + \beta_i P_{Gi} + \delta_i) \quad (Kg/h) \qquad (8)}$$

E_i: total emission (Kg/h); P_{Gi}: generation of unit (MW)

α_i , β_i, δ_i: emission coefficients of unit

n: number of generating units.

I.3. Combined Economic and Emission Dispatch

I.3.1 Definition

Redressing the economic load dispatch (ELD) challenges has a substantial emphasis on the power system's operation, planning, economic scheduling, and security.

The nonlinear constrained ELD problem is targeted to decrease the electric power generating cost with the optimal setting of concerned generating unit outputs, meeting the demands of whole unit and system limitations.

Generally, harmful emissions of fossil fuels are not handled properly by the conventional ELD, to resolve this issue, the combined effect of economic and emission dispatch CEED [8] has been emerged.

I.3.2. CEED Formulation

The key concern is to simultaneously reduce fuel costs and emissions while committing to equality and inequality limits. The CEED problem is dual-objective due to the independence of the cost and emission functions [8].

By combining two objective functions into one, it is possible to solve bi-objective problems (8).

The Emission Dispatch Problem can be mathematically represented as:

$$Min\left\{E = \sum_{i=1}^{ng} \mathrm{E}_i(P_{Gi})\right\} \qquad (9)$$

$$\mathrm{E}_i = \sum_{i=1}^{n} (\alpha_i P_{Gi}^2 + \beta_i P_{Gi} + \delta_i) + \eta_i \exp(\gamma_i P_{Gi}) \quad (Kg/h)$$

$(\alpha , \beta , \gamma , \eta, \delta)$ are the emission coefficients of the i units

$$PTC = F_T + P_f \times \mathrm{E}_i \qquad (10)$$

PTC is the pure total cost of the system, P_f is the penalty factor, E_i is total emmison

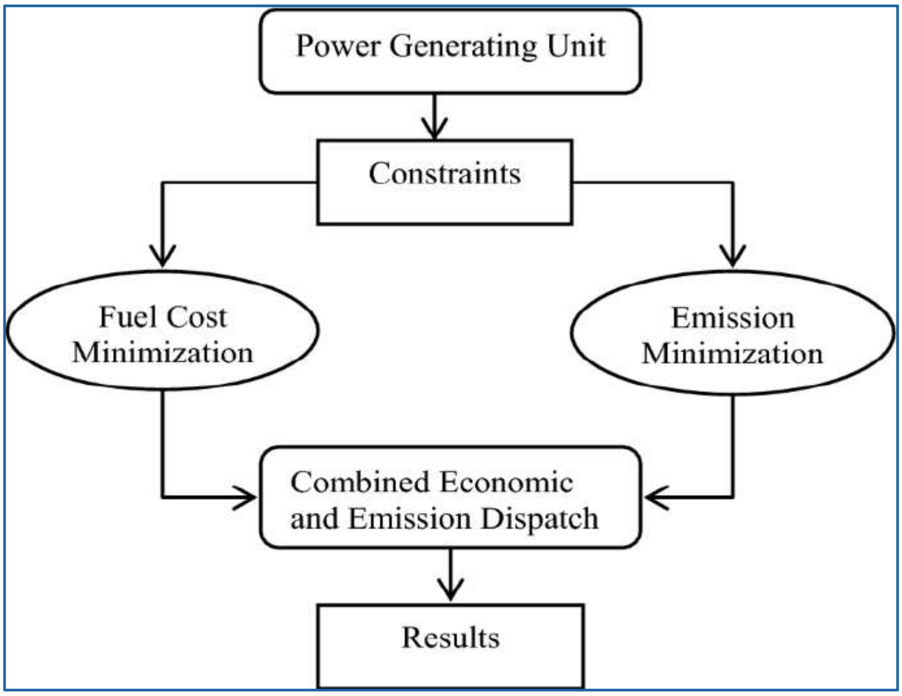

Figure 2 : solution for combined economic and emission dispatch problem.

I.4. The problem formulation considering VPE & MFO

I.4.1 Dispatch Formulation with Valve Point Effects

Another well-known model for cost function in PED problems is fuel cost function with Valve-Point Effect (VPE) (10), The generator cost function is obtained from data points taken during "heat run" tests, when input and output data is measured as the unit is slowly varied through its operating region.

Modern steam turbines with multi-valve exhibit larger variation in its fuel cost function, The valve opening process of multi-valve steam turbines produces a ripple-like effect in the heat rate curve of the generators.

therefore, "valve-point effect" are illustrated in "**Figure 3**", The significance of this effect is that the actual cost curve function of a large steam plant is not continuous but more important it is non-linear, The valve-point effects are taken into consideration in the ED problem by superimposing the basic quadratic fuel cost (2) and characteristics with the rectified sinusoidal component as follows:

$$F_i(P) = \sum_{i=1}^{n} (a_i P_{Gi}^2 + b_i P_{Gi} + c_i) + |e_i \times \sin(f_i(P_{GiMin} - P_{Gi}))| \quad (11)$$

$(a_i, b_i, c_i,)$: Are the cost coefficients of unit i.

(f_i, e_i): are the coefficients of VPE

Consequently, adjusting these parameters is an essential part to further increase the economic dispatch factors final accuracy.

A	Primary valve
B	Secondary valve
C	Tertiary valve
D	Quaternary valve
E	Primary valve

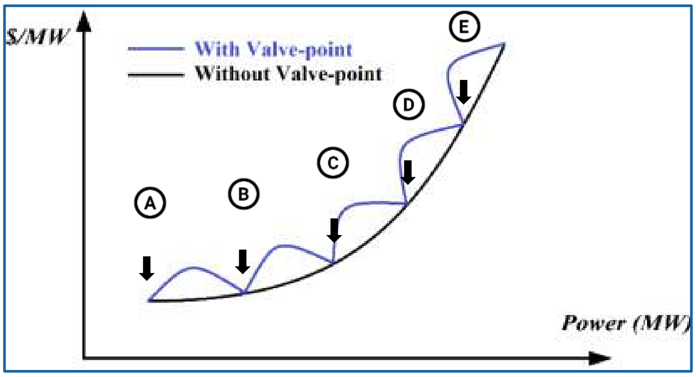

Figure 3 : fuel cost curve for PED with valve point effects (VPE).

I.4.2. Dispatch formulation with Multi Fuels Options

As real-world generation units are supplied with such multi-fuel sources as oil, naturel gas and coal, the input-output curve turns out to be represented by a piecewise quadratic cost function, Whereby, each segment should convey certain information [8] regarding the fuel type being used. In such a case, the optimizer must refer to the optimum power amount likely to be produced for each unit and so, the most economic fuel type that has.

fuel must have to be burnt to Enhance the objective function appears to be a hybrid function made up of several quadratic functions.

The fuel cost equation for a PED problem with only MFOs is as under in Equation (12).

$$F_i(P) = \begin{cases} a_{i1} + b_{i1}P_{Gi} + c_{i1}P_{Gi}^2 + , Fuel\ 1 , P_{Gi}^{Min} \leq P_{Gi} \leq P_{i1} \\ a_{i1} + b_{i1}P_{Gi} + c_{i1}P_{Gi}^2 , Fuel\ 2 \quad , P_{Gi}^{Min} \leq P_{Gi} \leq P_{i1} \\ , \\ ; \\ a_{ik} + b_{ik}P_{Gk} + c_{ik}P_{Gi}^2 , \ Fuel\ k, P_{ik-1} \leq P_{Gi} \leq P_{Gi}^{Max} \end{cases} \qquad (12)$$

$(P_{ik}^{Min}, P_{ik}^{Max})$ minimum & maximum power generations from units $(a_{ik}, b_{ik} , c_{ik})$cost coefficients of the generating unit consuming K_{th}fuel.

"Figure 4" Represents the fuel cost characteristics of a PED problem that considers only MFOs for generating units.

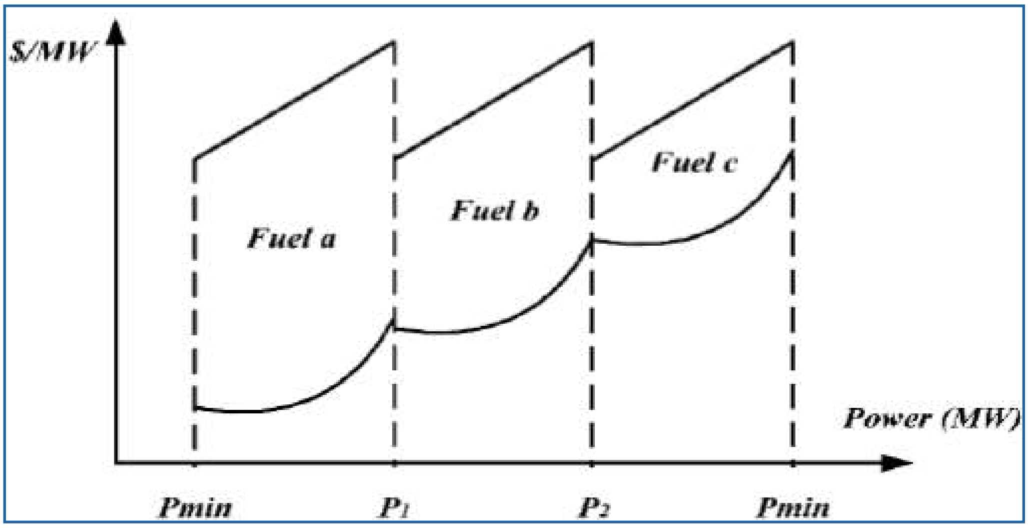

Figure 4 : fuel cost curve for PED problem with multiple fuel options (MFO).

I.4.3. Dispatch formulation with VPE and MFO

Optimizing economic dispatch with valve-point effects (11) and multi-fuels (12) requires advanced optimization techniques, considering factors like fuel availability, cost, plant efficiency, and emissions regulations.

By addressing these complexities, power generation systems can achieve improved efficiency and cost-effectiveness, while minimizing environmental impact.

The fuel cost equation for a PED problem modeling both [10] MFOs and VPE is as under in Equation (13)

$$F_i(P) = \begin{cases} a_{i1} + b_{i1}P_{Gi} + c_{i1}P_{Gi}^2 + |e_{i1} \times \sin(f_{i1}(P_{GiMin} - P_{Gi}))| \, , Fuel\ 1 \, , P_{Gi}^{Min} \leq P_{Gi} \leq P_{Gi1} \\ a_{i2} + b_{i2}P_{Gi} + c_{i2}P_{Gi}^2 + |e_{i2} \times \sin(f_{i2}(P_{GiMin} - P_{Gi}))| \, , Fuel\ 2 \, , P_{Gi}^{Min} \leq P_{Gi} \leq P_{Gi2} \\ , \\ , \\ a_{ik} + b_{ik}P_{Gi} + c_{ik}P_{Gi}^2 + |e_{ik} \times \sin(f_{ik}(P_{GiMin} - P_{Gi}))| \, , Fuel\ k \, , P_{Gi}^{k-k} \leq P_{Gi} \leq P_{GiMax} \\ . \\ . \end{cases} \quad (13)$$

This project proposed an incorporated cost model, which combines the valve-points and the fuel changes into one **"Figure 5"**.

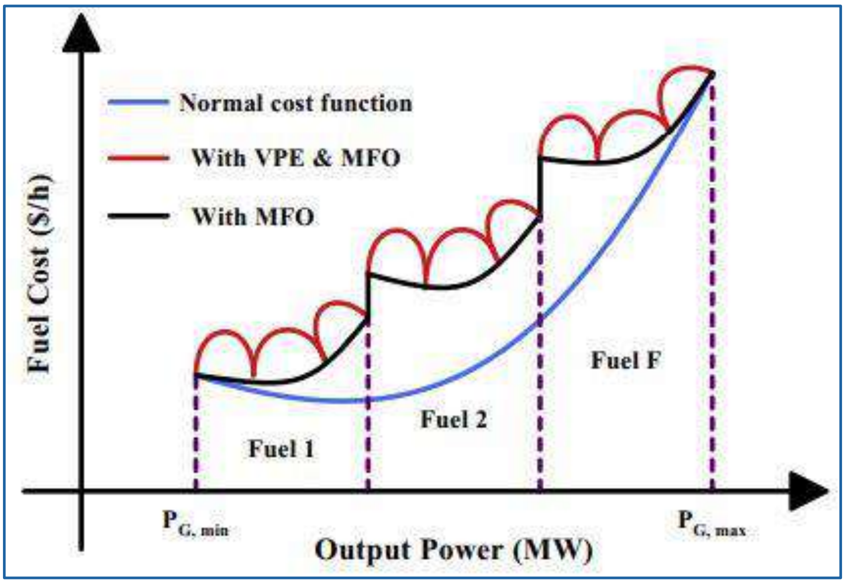

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Figure 5 : fuel cost curve with VPL and MFO impacts.

Conclusion

Economic emission dispatch (EED) With valve-point effects (VPE) and multi-fuel options (MFO) is an optimization problem that aims to minimize the total operating cost of a power system while meeting the load demand and satisfying the emission constraints, considering the non-smooth and discontinuous cost functions of the generators due to valve-point effects and the ability of generators to use different types of fuels.

Solutions that require these factors are necessary for optimizing power generation systems and ensuring reliable and cost-effective electricity supply, the performance of the power system can be enhanced by considering valve-point effects and multi-fuel options in economical emission dispatch. A comprehensive approach to EED that combines accurate mathematical models [11], advanced optimization algorithms, and real-world constraints can lead to better dispatch results by minimizing both fuel cost and environmental impact, while accommodating the complexities introduced by valve-point effects and multi-fuel options.

Chapter II

Adaptive Gaining-Sharing Knowledge Based Algorithm

Introduction

The nature of gaining and sharing knowledge in algorithms can be characterized as a multifaceted, dynamic process that involves the acquisition, development, dissemination, and application of information within various domains. It encompasses a range of cognitive and social processes, including learning, teaching, collaboration, and innovation, this intricate interplay between individual minds and collective intelligence forms the foundation for advancing human understanding and refining algorithmic solutions [19], gaining knowledge in algorithms typically begins with learning fundamental principles, data structures, and computational techniques. This process often entails studying existing algorithms, analyzing their strengths and weaknesses, the gaining sharing knowledge-based optimization algorithm is a technique used to optimize complex systems, It involves sharing knowledge among various parts of the system to improve overall efficiency[20], The algorithm works by using a hybrid approach that incorporates elements of both genetic algorithms and swarm intelligence, The process involves creating a population of potential solutions, evaluating each of these solutions, and then using knowledge from the best solutions to improve the rest of the population, This process is repeated until a satisfactory solution is found, Adaptive Gaining-Sharing Knowledge Based Algorithms lie in their complexity, maturity, capability, interdisciplinary integration, and ability to handle ambiguity and uncertainty. The presented algorithm (APGSK)[22] is tested on a very recent benchmark testbed on bound constrained numerical optimization that composed of distinct challenging optimization problems with different dimensions

II.1. Optimization Techniques

optimization techniques for economic dispatch strive to find the most cost-effective power distribution among generating units while meeting system constraints. Numerous approaches exist, each with its strengths and weaknesses. The choice of optimization technique depends on factors such as system size, nonlinearity, constraint types, and required accuracy.

The objective of optimization is to identify the optimal solution from a multitude of solutions that exist within the problem space. Various techniques have been developed to attain this objective, which can be broadly categorized into traditional and advanced techniques [18].

Traditional techniques : Deterministic optimization algorithms comprise of specific rules for transitioning between solutions as an example of these algorithms:(Linear/Nonlinear/Integer/Dynamic/Quadratic) program-Ing Calculus of variation, Calculus methods.

Advanced techniques : stochastic optimization algorithms consist of rules with probabilistic transition, as an example of these algorithms:

Particle Swarm Optimization (PSO), Bat Optimization Algorithm (BOA), Whale optimization algorithm (WOA) elephant herding optimization (EHO), Gaining Sharing Knowledge Base Algorithm (GSK), and many others algorithms.

The traditional techniques are missing several aspects that can be found in the advanced techniques, and the advanced techniques also have some restrictions a comparison of the many techniques for optimization.

II.2. Tree of optimization techniques

Evolutionary-based techniques, programming-based techniques, and intelligent-based techniques are all distinctive approaches to solve complex optimization and search problems (fig 3).

- **Evolutionary-based optimization techniques :** techniques that produce optimal individuals based on the process of gradual improvement and change, the better generation affected based on the natural select, mutation and crossover operators, examples of these techniques are genetic algorithm (GA), Quantum evolutionary algorithm (QEA), and Backtracking optimization algorithm (BOA) and others.
- **Programming based optimization techniques :** optimizations that represent the population as a decision tree and Each individual(program) is evaluated according to its capacity to tackle the optimization problem from these techniques are Genetic Programming (GP)Cartesian Genetic Programming (CGP) and others.
- **Intelligent based optimization techniques :** techniques that are molded by the natural behavior of swarms of intelligent animals, where each individual has its own intelligence ability, and a combination of all individuals constructs a powerful tool to solve complex problems. these techniques may likewise imitate human behavior in its physical and non-physical activities. These techniques treat a population as randomly generated groups of solutions, with each group having a leader (agent) that guides it through successive generations until the optimal global solution is found. examples of these techniques are Particle Swarm Optimization (PSO), Bat Optimization Algorithm (BOA), Whale optimization algorithm (WOA) elephant herding optimization (EHO), Gaining Sharing Knowledge Base Algorithm(GSK), and many others algorithms.

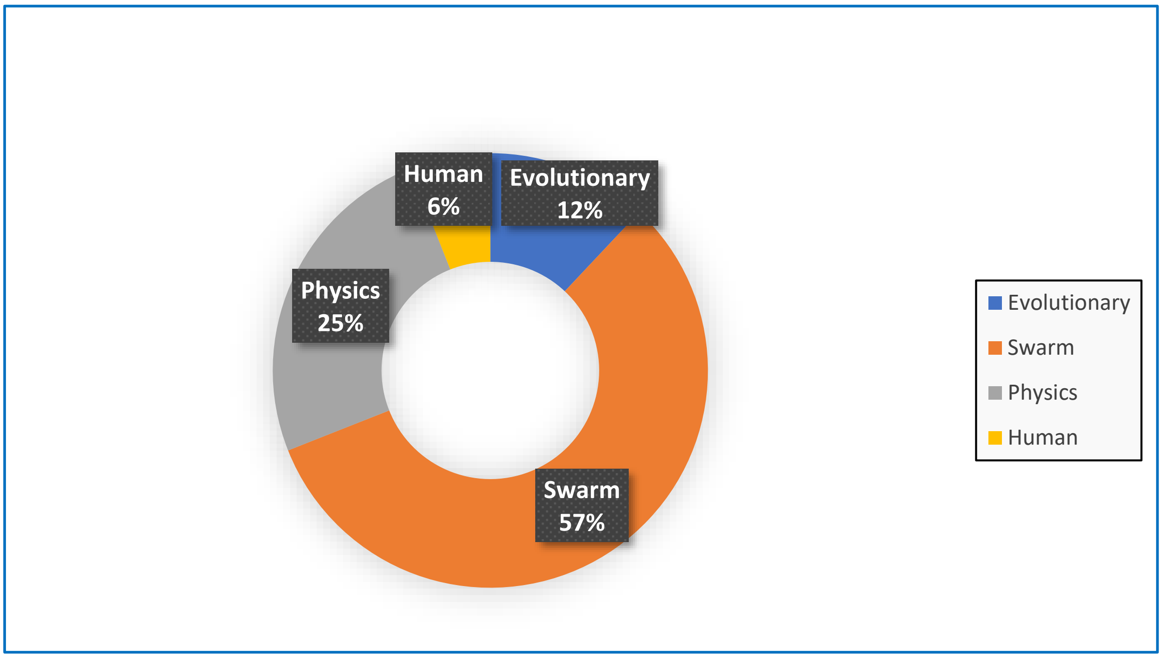

Figure 6 : percentage share for each category in the overall meta-heuristic algorithms.

Due to interacting with larger networks each person has their own knowledge in different fields that can be significantly enhanced by gaining it from others. last few decades there has been an improvement in the development of human-based algorithm optimization, which has a good structure and techniques in many fields of engineering.

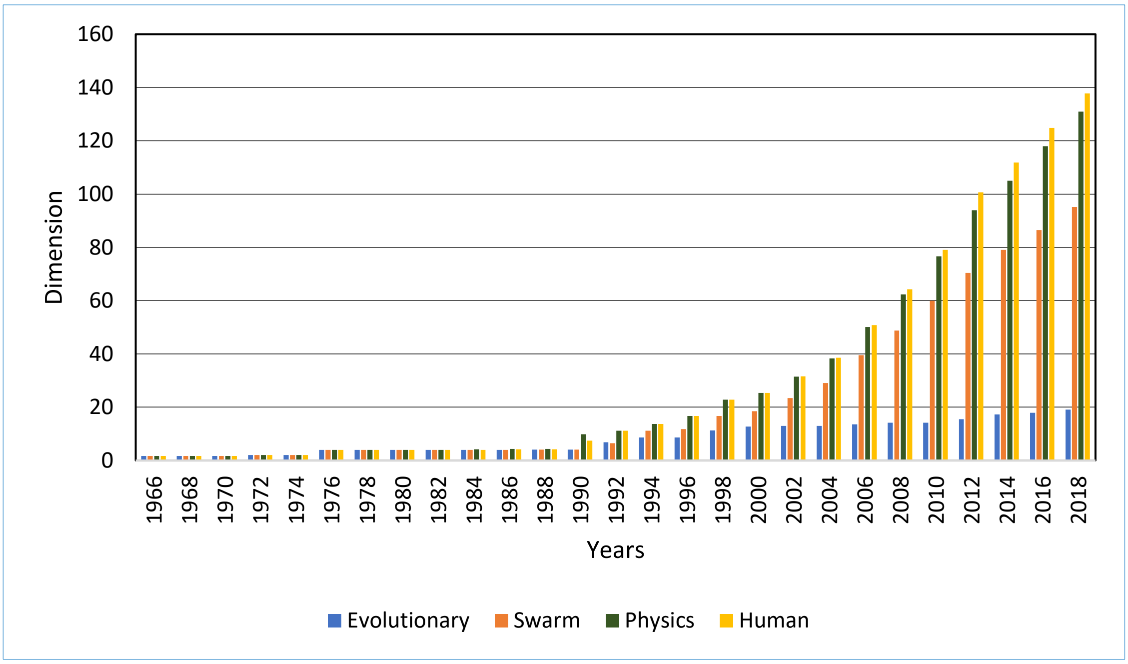

Figure 7 : percentage share for each category in the overall meta-heuristic algorithms.

II.3 Gaining Sharing Knowledge Algorithm

Gaining and sharing knowledge is a crucial aspect of optimization. This procedure includes the collection, analysis, and dissemination of data Population Users to enhance the efficacy and efficiency of decision-making processes. In this context "gaining knowledge" refers to acquiring new information or insights which is data collected from previous practices can be used to enhance performance. In contrast, sharing knowledge involves disseminating this information to others in order to facilitate collaboration and problem-solving.

Figure 8 : classification of optimization techniques.

II.4 GSK Algorithm Construction

GSK is a metaheuristic technique proposed by Mohamed et al. [20] that based on population and a nature inspired and it considered the behavior of human life spin. this algorithm characterized by its robustness, the overall performance is stable(robust) even the dimension increase, good convergence speed, the high-quality problem solution even with high dimension problems, complex problems and real time optimization problems, like others optimization algorithm [21].

Constrained optimization problem [22] could be formulated (12) as:

$$Min\ f\ (X)\ ; X = [x_1, x_2, \dots \dots \dots, x_{Dim}]$$

$$Subject\ to.\ g_i\ (X) \leq 0; i = 1,2, \dots, m \qquad (12)$$

$$X\ \in \left[\alpha_p, \beta_p\right];\quad p = 1,2, \dots \dots, Dim$$

where, f represents the objective function; $X = [x_1, x_2, \ . \ . \ . \ , x_{Dim}]$ represents the decision variables; $g_i\ (X)$ represents the inequality constraints and α_p, β_p represent the lower and upper boundaries of the decision variables, respectively. Dim is the number of dimensions of an individual, In case the problem is to maximize the objective function, then we can consider minimization as (−1 × Maximization).

The structure of gaining-sharing knowledge optimization involves It is based on two vital stages.

1. Junior (beginners) Gaining and Sharing stage.

2. Senior (experts) Gaining and Sharing stage.

All people gain knowledge and share it with others throughout their lifetime. Early middle-aged individuals gain knowledge from their small connections, such as family members and relatives, and wish to share their views and opinions with others who may or may not be members of their group. Similarly, people in their middle and later years gain knowledge through interaction with their colleagues, friends, etc. [20] They have the experience necessary to assess and categorize individuals as good or bad. In addition, they share their views or opinions with knowledgeable or appropriate individuals so that their knowledge can be expanded.

The process, as mentioned above, can be mathematically formulated in the following steps [22]:

Step 1: For the optimization procedure to begin, an initial population (solutions) is required. A random population is generated considering the following boundary constraints:

$$x_{tp}^{0} = \alpha_p + rand_p(\beta_p - \alpha_p) \quad (13)$$

where t represents the number of people in the population; $rand_p$represents a random number generated from a uniform distribution between [0,1]; β_p is the upperbound of the decision variable, and α_p is the lower bound.

Step 2 : At the beginning of the search, the number of dimensions for the junior and senior stage should be computed. The number of dimensions that should be changed or updated during both the stages must set on, and it is calculated by a non-linear decreasing and increasing equation (14) & (15).

$$Dim_j = Dim \times \left(\frac{Gen^{Max} - G}{Gen^{Max}}\right)^k \quad (14)$$

$$Dim_s = Dim - D_j \quad (15)$$

k is a positive integer greater than zero that represents the learning rate, which monitors the experience rate. Dim_{junior} is the dimension of the junior phase, while Dim_s is the dimension of the senior phase, G is a counter for generations, while Gen^{Max} is the highest number of generations.

Step 3: Junior Sharing Knowledge Stage: In this stage, early-middle aged individuals gain knowledge from their small networks, They share their opinions or skills with individuals who may or may not be a part of their group out of a desire to learn about them Consequently, individuals are informed as follows:

1. According to objective function values, the individuals are arranged in ascending order as $X_i, \ldots, X_{i-1}, X_i, X_{i+1}, \ldots, X_{worst}$.

2. For every X_i (i = 1, 2,…… N_p), select the nearest best (X_{i-1}) and worst X_{i+1} to gain the knowledge, also select randomly (X_r) to share the knowledge. Therefore, the updated new individual is as (16).

$$X_{ij}^{New} = \begin{cases} X_i + K_f[(X_{i-1} - X_{i+1}) + (X_r - X_i)], If\ f_{(Xr)} < f_{(Xi)} \\ X_i + K_f[(X_{i-1} - X_{i+1}) + (X_i - X_r)], Otherwise \end{cases} \quad (16)$$

Where, $K_f > 0$ is the knowledge factor.

the pseudo-code is presented in Below Code

For i=1:NP
  For j=1: Dim_j
    $if\ f\ rand\ \leq k_r\ (knowledge\ ratio)$
      $if\ f_{(Xr)} < f_{(Xi)}$
      $X_{ij}^{New} = X_i + K_f[(X_{i-1} - X_{i+1}) + (X_r - X_i)]$
      $else$
      X_{ij}^{New}=$X_i + K_f[(X_{i-1} - X_{i+1}) + (X_i - X_r)]$
     $End(if)$
      $Else\ X_{ij}^{New}$=X_{ij}^{old}
$End(if)$
$End(for\ j)$
$End(for\ i)$

Pseudo - code 1 : for junior gaining-sharing-knowledge phase.

Step 4: Senior Sharing Knowledge Stage: The influence of other individuals (suitable or inappropriate) on the relevant individual is implicated, improving individuals could be determined as follows:

The candidates of the population are divided into three categories.

(Best individuals, Middle individuals, and Worse individuals).

after sorting individuals in ascending order (based on the objective function values).

- Best individual = $100_{P\%}(X_{p-best})$,
- Middle individual = $(NP-2) \times 100_{P\%}(X_{middle})$,
- Worst individual = $100_{P\%}(X_{p-worst})$,

Best individual	Middle individual	Worst individual
$100_{P\%}(X_{p-best})$	$(NP-2) \times 100_{P\%}(X_{middle})$	$100_{P\%}(X_{p-worst})$

2. For every individual X_i, choose two random vectors of the top and bottom $100_{P\%}$ individual for gaining part and the third one (middle individual) is chosen for the sharing part.

Therefore, the new individual is as :

$$X_{ij}^{New} = \begin{cases} X_i + K_f\left[\left(X_{p-best} - X_{p-worst}\right) + (X_{middle} - X_i)\right], If\ F_{(X_{middle})} < F_{(Xi)} \\ X_i + K_f\left[\left(X_{p-best} - X_{p-worst}\right) + (X_i - X_{middle})\right], Otherwise \end{cases} \quad (17)$$

where, $p \in [0, 1]$ and p =0.1, 10% of NP is suitable

1. For i=1:NP
2. For j=1: Dims
3. $if\ f\ rand\ \leq k_r\ (knowledge\ ratio)$
4. $if\ f_{(Xi)} < f_{(Xm)}$
5. $X_{ij}^{New} = X_i + K_f[(X_{p-best} - X_{p-worst}) + (X_{middle} - X_i)]$
6. $else$
7. $X_{ij}^{New}{=}X_i + K_f[(X_{p-best} - X_{p-worst}) + (X_i - X_{middle})]$
8. $End(if)$
9. $Else\ X_{ij}^{New}{=}X_{ij}^{old}$
10. $End(if)$
11. $End(for\ j)$
12. $End(for\ i)$

Pseudo - code 2 : for senior gaining-sharing-knowledge phase.

II.5 GSK algorithm code

The Code of Gaining and Sharing Knowledge algorithm is an efficient tool that aims to optimize the entire process of accumulating knowledge and sharing it with others, This algorithm is built upon the principles of machine learning, language processing, which enables it to determine patterns and insights that can help users learn more efficiently[22].

1. Begin
2. G=0, initialize parameters: N,k_f,k_r,k and p
3. $Creat\ a\ random\ initial\ population\ x_i, i = 1,2, \ldots \ldots N$
4. $Evaluate\ f(x_i), \forall i, i = 1,2, \ldots \ldots N$
5. $For\ G = 1\ to\ GEN^{max}$
6. $Compute\ the\ number\ of$

   $(Gainded\ and\ shared\ dims, of\ both\ phases)$

   $using\ experience\ eqs, (2), (3);$
7. $//junior\ gaining\ - sharing\ knowledge\ phase//$
8. $//senior\ gaining\ - sharing\ knowledge\ phase//$
9. $If\ (x_{ij}^{New} \leq x_{ij}^{old}),$

   $x_i^{old}{=}x_i^{New}, f\left(x_i^{old}\right) = f(x_i^{New})$

   $end\ //\ update\ each\ vector$
10. $End\ For \ldots \ldots N$
11. $End\ For \ldots \ldots G$
12. $\boldsymbol{End}\ For \ldots \ldots Begin$

    $end\ //\ update\ global\ best$
13. $End\ For \ldots \ldots N$
14. $End\ For \ldots \ldots G$
15. $\boldsymbol{End}\ For \ldots \ldots Begin$

Pseudo - code 3 : for gsk algorithm

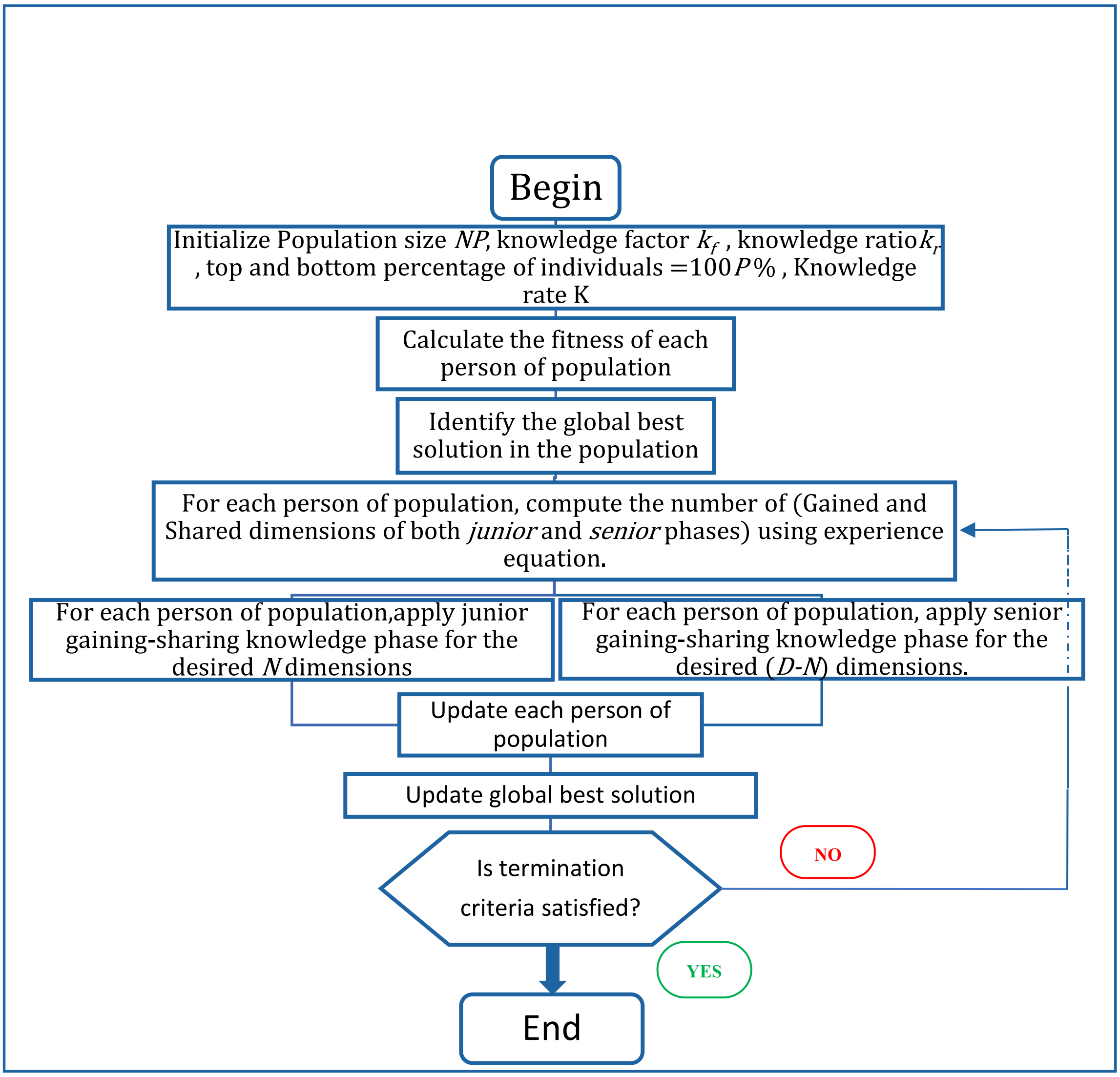

Figure 9 : flowchart of gsk algorithm

II.6 Adaptive GSK settings

The values of Knowledge $[k, k_f, k_r, N]$ Factor k, Knowledge Ratio k_r, Knowledge Rate k_r and number Of population N are important parameters that can be adjusted to optimize the performance of the algorithm[22], choose the values of its control parameters, the Gaining and Sharing Knowledge algorithm can use a simple trial-and-error approach. The algorithm starts with an initial set of control parameters and then tests them to see if they lead to better results than other possible sets of control parameters, Otherwise the algorithm tries a different set of control parameters until it finds a set that leads to better results.

```
Begin
  G=0, initialize parameters Setting Pool,Initialize Kw_p
    while nfes < max _nfes
      If(nfes > 0.1 × max _nfes)
        Update Kw_p
      End if
      Assign one setting to each individual according to Kw_p
          x_i^new = Generate new individuals using GSK
          Calculate the improvement of each setting
    End While
End Begin
```

Pseudo - code 4 : code for the adaptation process.

II.6.1 Control adaptive settings ($\boldsymbol{k_f}$ & $\boldsymbol{k_r}$)

Initially, the two parameters and the probability parameter Kw_p are selected from a pool of candidates to be adapted. The pool used to determine optimal values $(k_f\ ,\ k_r)$: [(0.1, 0.2), (1.0, 0.1), (0.5, 0.9), and (1.0, 0.9)] applied during first *50%* of *MAXNFE* while the another pairs: [(−0.15, 0.2), (−0.05, 0.1), (−0.05, 0.9), and (−0.15, 0.9)] will be activated after *50%* of *MAXNFE* with a probability of less than (0.3) for increasing the population's genetic diversity to assure escape from the local optimal state, and reduce the odds of inactivity, The probability parameter Kw_p contains the probabilistic parameter p for each of the noted sets of settings. Thus, each population member will receive one setting based on its probability parameter p.

The probability parameter adaptation Kw_p begins after 10% of function evaluations. The probability parameter's adjustment varies with each setting's performance by the following formula:

$$\omega_{ps} = \sum_{i=1}^{n} f\left(x_i^{new}\right) - f\left(x_i^{old}\right) \quad (18)$$

where ω_p represents the sum of the differences between old fitness value and the new fitness value for every individual belonging to parameter setting (ps), (f) represents the fitness function, $(x_i^{new})$is the new solution, (x_i^{old}) is the old solution, and (n) represents the number of solutions that belong to the parameter setting (ps)[22], After that, the improvement rate,(Δps) could be calculated for each parameter setting by:

$$\Delta ps = max\ (0.05, \omega_{ps}/sum(\omega_{ps})) \quad (19)$$

To ensure that each parameter setting has a chance of being chosen, 0.05 is used to convey the minimum probability that could be assigned to each parameter setting, the improvement rate (Δps) for each parameter setting is used for updating Kw_p due to the following formula:

$$Kw\_P_{g+1} = (1-c)Kw_{P_g} + c \cdot \Delta ps \quad (20)$$

where C represents the rate of learning. Utilizing a constant learning rate, cumulative knowledge related to the performance of every factor setting is leveraged.

II.6.2 Population Size Reduction

In order to improve AGSK overall performance Non-Linear Population Size Reduction (NLPSR)[22], uses the number of errors and the average magnitude of the errors to determine how many problems an agent should try to solve in order to obtain a certain level of error reduction, The algorithm works by iteratively selecting agents with high population size and dividing them into smaller subpopulations. These smaller subpopulations then repeat the same process until they have reduced their error rates below a certain threshold, This approach allows for more efficient use of computational resources and can be used to generate problem instances with larger error magnitudes than others, Non-linear function in APGSK below:

$$N_{G+1} = round[(N^{min} - N^{init}) \times ((NFE/MAX_{NFE}))^{(1-NFE/MAX_{NFE}))} + N^{init} \quad (21)$$

NFE	Current number of functions evals
MAX_{NFE}	Max allowable number of functions evals
N^{init}	Size of the population initially generated

$N^{min} = 12$ is the minimum number of candidates required for APGSK to ensure that both the best and worst partitions contain multiple individuals.

II.6.3 Settings of knowledge Rate *K*

In fact, the diversity of a population must be considered when simulating the process of acquiring and exchanging knowledge during the human life span for a specific population, Therefore, the knowledge rate k must take into consideration both scenarios, the first scenario when $K \in (0, 1)$, and the second scenario when,

$K \geq 1$ with probability of NFE/MAX_{NFE}. So, for each individual in the population, if $rand > (NFE/MAX_{NFE}), K = 0.5$ $else$ $K = 2$.

Conclusion

In order to solve the Economic Load Dispatch (ELD) problem, which aims to minimize the total cost of power generation while meeting the power demand and system constraints of units, using the Adaptive Gaining-Sharing Knowledge Based Algorithm, multiple phases must be taken. Based on the principles of machine learning and optimization, these steps involve collecting data, training the computation, and implementing it in the power system, beginning with defining the power boundaries based on the capacity and operating characteristics of the power system and continuing with the collection of historical data on power generation. This information is used to train the machine learning algorithm and make predictions, as well as to integrate the algorithm into the control system of the power grid and configure it to receive data on power demand and generator output. Once the algorithm is operational, it can be monitored and modified to enhance its performance as required.

Chapter III

Simulation Results and Discussions

Introduction

In this chapter of simulation the AGSK has been implanted to fit our problem which is a electrical dispatching for several system cases with changes of one to another considering on the total of all cases study system with power demande, to valve point effects, transmission losses and emission all the 4 system cases, the cost fuel quadratic function is a function that takes into account the cost of fuel and the efficiency of the system, and uses this information to determine the optimal fuel consumption rate.to implement the cost fuel quadratic function using adaptive gaining sharing knowledge, it is necessary to first gather data on the system's fuel consumption and efficiency from articles. once the model has been created, adaptive gaining sharing knowledge can be used to optimize the system's fuel consumption. this involves adjusting the fuel consumption rate based on the system's current operating conditions, such as the load on the system which relay to transmission losses if it was considerate ,furthermore the AGSK preform on good stability by compiling the problem constraint and boundaries on random but on scale that get the best solution .

III.1 Implementing AGSK for solving ed problem:

The AGSK algorithm is used to distribute demand among generators in a power system, the algorithm is designed to balance the extraction of electricity from each generator with the demand from other generators and transmission lines while also accounting for the availability of resources.

Equation N °	Formulas
(2)	$F_T = \sum_{i=1}^{n}(a_i P_{Gi}^2 + b_i P_{Gi} + c_i) \ \frac{\$}{h}$ $[\,quadratic\ fuel\ cost\ function\,]$
(3)	$\sum_{i=1}^{n} P_{Gi} = P_D + P_L \ \ MW$ $[Power\ balance\ constraints]$
(4)	$P_L = \sum_{i=1}^{n}\sum_{i=1}^{n} P_i B_{ij} P_j + \sum_{i=1}^{n} B_{0i} P_i + B_{00}$ $[Transmission\ constraints\ ]$
(5)	$P_{Gi\,Min} \leq P_{Gi} \leq P_{Gi\,Max}$ $[Generator\ capacity\ constraints\,]$
(6)	$ax(P_i^{Min}, P_i(t-1) - DR \leq P_i(t)$ $P_i \leq (Min(P_i^{Max}, P_i(t-1) + UR_I)$ $[ramp\ rate\ constraints]$,
(7)	$\boldsymbol{P_i^{Min} \leq P_i \leq P_{i,1}^{Low} : P_{i,k-1}^{Up} \leq P_i \leq P_{i,k}^{Low} : P_{i,ni}^{Up} \leq P_i \leq P_i^{max}}$ [POZ $constraint$]
(8)	$E_i(P_{G_i}) = \sum_{i=1}^{n}(\alpha_i P_{Gi}^2 + \beta_i P_{Gi} + \delta_i) \ \ (Kg/h)$ $[quadratic\ emission\ function]$
(10)	$PTC = F_T + P_f \times E_i$ $[\,The\ bi-objective\ CEED\ function\,]$
(11)	$F_i(P) = \sum_{i=1}^{n}(a_i P_{Gi}^2 + b_i P_{Gi} + c_i) + \lvert e_i \times \sin(f_i(P_{GiMin} - P_{Gi}))\rvert$ $[quadratic\ fuel\ cost\ function\ with\ VPL]$
(13)	$F_i(P) = \begin{cases} a_{i1} + b_{i1}P_{Gi} + c_{i1}P_{Gi}^2 + \lvert e_{i1} \times \sin(f_{i1}(P_{GiMin} - P_{Gi}))\rvert, Fuel\ 1, P_{Gi}^{Min} \leq P_{Gi} \leq P_{Gi1} \\ a_{i2} + b_{i2}P_{Gi} + c_{i2}P_{Gi}^2 + \lvert e_{i2} \times \sin(f_{i2}(P_{GiMin} - P_{Gi}))\rvert, Fuel\ 2, P_{Gi}^{Min} \leq P_{Gi} \leq P_{Gi2} \\ , \\ , \\ a_{ik} + b_{ik}P_{Gi} + c_{ik}P_{Gi}^2 + \lvert e_{ik} \times \sin(f_{ik}(P_{GiMin} - P_{Gi}))\rvert, Fuel\ k, P_{Gi}^{k-k} \leq P_{Gi} \leq P_{GiMax} \end{cases}$ $[quadratic\ fuel\ cost\ function\ with\ VPL +\ MFO]$

To implement the AGSK algorithm, it would be necessary to collect data on the available energy sources, such as petroleum and gas, as well as consumer demand for electricity. One effective approach to solving this problem is to use algorithm optimization techniques, algorithm optimization involves choosing an appropriate algorithm and implementing it using software tools such as MATLAB. The algorithm takes the mathematical model of the problem as input and provides a solution that minimizes the cost of generating power while satisfying the demand for electricity.

III.2 Parameters selection of AGSK:

The parameters of the suggested AGSK algorithm are chosen by executing different trials for each test system. population size is between 50 to 140 with five Run Number To optimize the solutions as far best and with less time.

III.3 Data systems:

The proposed AGSK method is utilized to address ELD problems in four separate test cases and compared to various types of other heuristic optimization techniques.

AGSK algorithm has been implemented using the MATLAB software Version 9.10 b on a personal computer (Processor: intel Core i5-7200U 2.7Ghz, memory: 8GB Storage: 1TB) with population size(NP) changes from 50 to 140 & 5 runs number & MAXNFES 200000 to optimize the solutions for System cases.

III.3.1 Test system 1:

In this test system, there are six generating units with a total power demand of 1263 MW, This test system considers ramp rate limits, and POZ effects and transmission loss [23], The system data is given in **”Table 1”** & **“Table 2”** taken from [24].

Table 1 : generating unit capacity and coefficients case 1

$Unit$	P_i^{Min}	P_i^{Max}	a_i (\$)	$b_i(\$/MW)$	$c_i(\$/MW^2)$
1	100	500	240	7.0	0.0070
2	50	200	200	10.0	0.0095
3	80	300	220	8.5	0.0090
4	50	150	200	11.0	0.0090
5	50	200	220	10.5	0.0080
6	50	120	190	12.0	0.0075

Table 2 : ramp rate limits and prohibited zones of generating units case 1.

$Unit$	P_i^0	$UR_i\ (MW/h)$	$DR_i\ (MW/h)$	$Prodhibted\ zones(MW)$
1	440	80	120	[350 380] [350 380]
2	170	50	90	[140 160] [140 160]
3	200	65	100	[210 21] [210 240]
4	150	50	90	[110 120] [110 120]
5	190	50	90	[140 14] [140 150]
6	110	50	90	[100 105] [100 105]

transmission loss coefficients.

$$\boldsymbol{B_{ij}} = \mathbf{10^{-2}} \times \begin{bmatrix} 0.0017 & 0.0012 & 0.0007 & -0.0001 & -0.0005 & -0.0002 \\ 0.0012 & 0.0014 & 0.0009 & 0.0001 & -0.0006 & -0.0001 \\ 0.0007 & 0.0009 & 0.0031 & 0.0000 & -0.0010 & -0.0006 \\ -0.0001 & 0.0001 & 0.0000 & 0.0024 & -0.0006 & -0.0008 \\ -0.0005 & -0.0006 & -0.0010 & -0.0006 & 0.0129 & -0.0002 \\ -0.0002 & -0.0001 & -0.0006 & -0.0008 & -0.0002 & 0.0150 \end{bmatrix}$$

$$\boldsymbol{B_{oi}} = \mathbf{10^{-5}} \times [-0.3908 \quad -0.1297 \quad 0.7047 \quad 0.0591 \quad 0.2161 \quad -0.6635]$$

$$\boldsymbol{B_{oo}} = \mathbf{10^{-2}} \times 0.0056$$

For the power demand of 1263 MW, the comparison of the proposed AGSK with various optimization techniques in literature been performed in **"Table 3"** and **"Table 4"**, It is evident from **"Table 3"** compares the minimum, mean, and maximum fuel costs, standard deviation obtained by the AGSK approach with the others techniques,

"Table 4" show The optimal generation schedule, fuel cost, and transmission loss obtained by the AGSK and other heuristic approaches

Table 3 : Comparison of results in the 6-unit system.

Techniques	Minimum ($)	Average ($)	Maximum ($)	Std.dev
GA	15459	15469	15469.00	NA
MTS	15450.06	15451.17	15453.64	0.93
PSO-LRS[24]	15450	15454	15454	NA
PSO[24]	15450	15465.83	15492.00	6.82
BSA[40]	15449.898	15449.90	15449.91	0.0010
TSA[46]	15451.63	15462.26	15506.451	5.98
CBA[41]	15450.23	15454.76	15518.66	2.965
FA[27]	15450.51	15452.53	15458.44	2.048
CMFA[27]	15449.887	15449.89	15450.48	0.083
AGSK	**15444.19**	**15444.21**	**15444.583**	**0.05473**

Table 4 : the system units power in case 1.

Pg (MW)	GA	MTS	PSO-LRS	PSO	TSA	CBA	FA	CMFA	AGSK
Pg 1	474.8066	448.1277	446.96	447.444	447.497	447.4902	449.3651	447.4187	**446.7151**
Pg 2	178.6363	172.8082	173.3944	173.343	173.3221	173.3308	182.252	172.8255	**173.1493**
Pg 3	262.2089	263	262.3436	263.3646	263.4745	263.4559	254.2904	264.0759	**262.7692**
Pg 4	134.2826	136.9605	139.512	139.1279	139.0594	139.0602	143.4506	139.2469	**143.5576**
Pg 5	151.9039	168.2031	164.7089	165.5076	165.4761	165.4804	161.9682	165.6526	**163.8216**
Pg 6	74.1812	87.3304	89.0162	87.1698	87.128	87.1409	86.0185	86.7652	**85.3544**
Total power (MW)	1276.03	1276.023	1275.94	1275.95	1276.01	1275.958	1277.345	1275.9848	**1275.419**
PLoss(MW)	13.0217	13.0205	12.9361	12.9571	12.9584	12.9583	14.3449	12.9848	**12.419**
Minimum cost ($/h)	15459	15450.06	15450	15450	15450	15449.89	15451.63	15450.23	**15444.19**

For the 6 Units test system, it can be noticed that the proposed AGSK algorithm has done the best solution so far decreasing the total fuel cost of the total system compared to other optimization techniques [27], considering prohibited operating zones, ramp rate limits, transmission losses AGSK did find the lowest cost of fuel with **15444,19 $** among all others compared techniques which they was higher then AGSK those other Costs proves the superiority performance of the proposed algorithm shows that the AGSK approach obtains better quality solutions than the compared algorithms and has good stability .

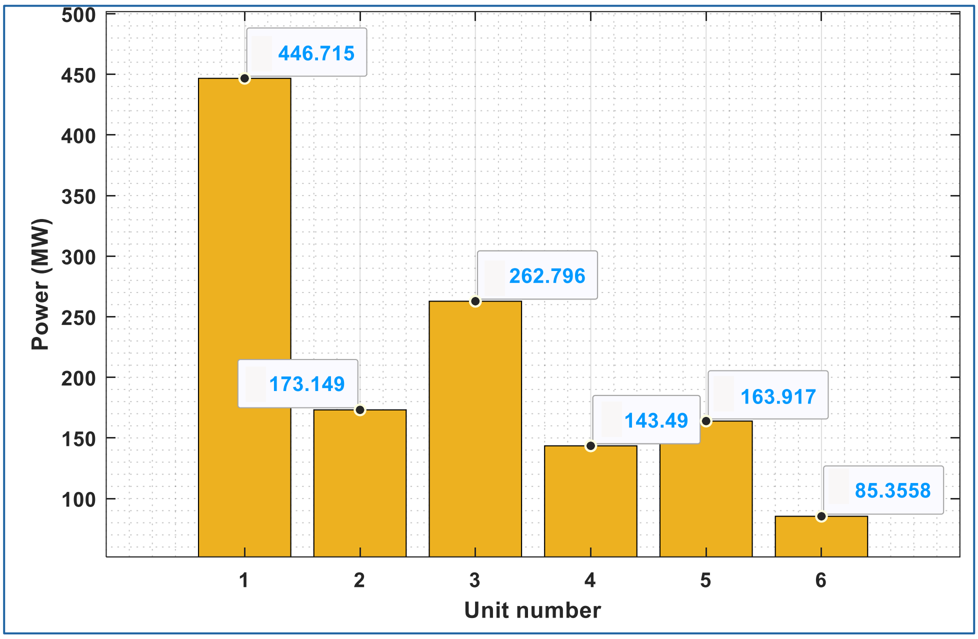

Figure 10 : power genereated from each unit for system 1

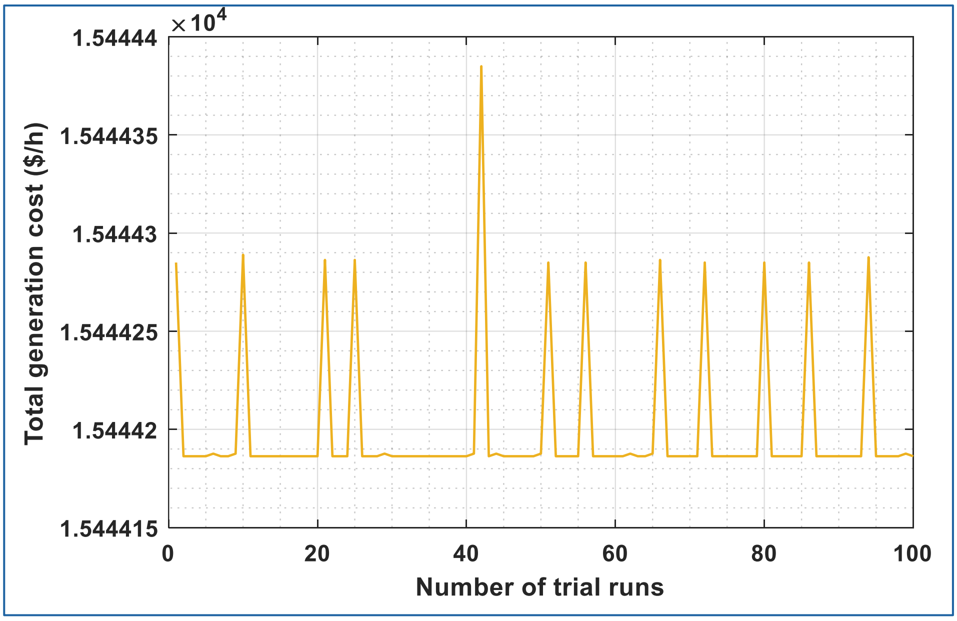

Figure 11 : Dissemination of fuel costs of the AGSK technique for system 1.

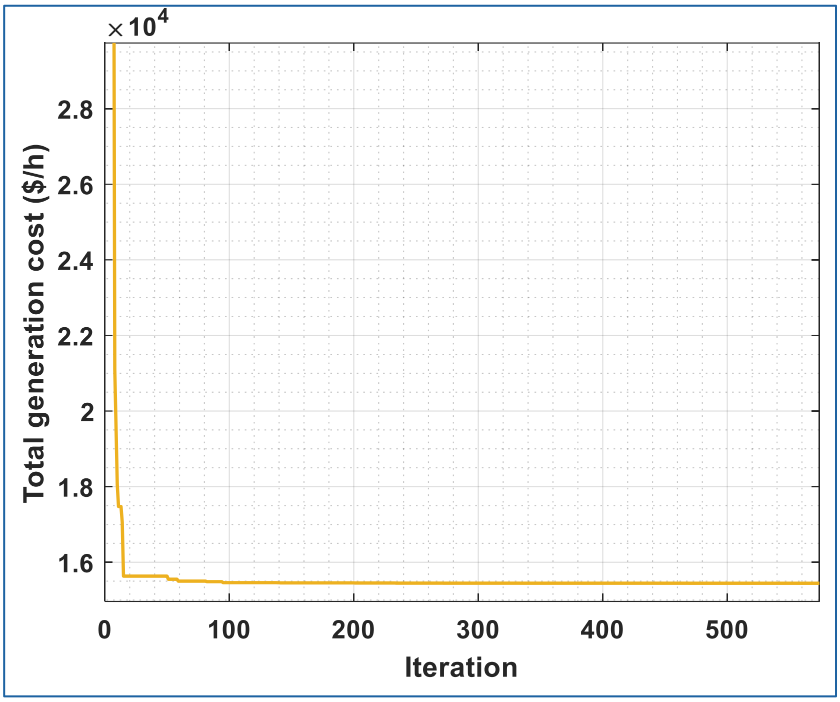

Figure 12 : convergence characteristic of the AGSK for system 1.

III.3.2 Test system 2

The test system is comprised of 13 generators featuring VPL effects without transmission losses. The power demand is 1800 MW in terms of solution quality, robustness, and various indices including minimum, mean, and maximum costs, and standard deviations of fuel cost values, the algorithm's results are compared with those of other reported algorithms, system data obtained from [25], the system data are below in **"Table 5"**, Results are in **"Table 6"** & **"Table 7"**.

Table 5 : data system for 13-unit with valve-point loading.

Unit	P_i^{Min}	P_i^{Max}	*FUEL-COST COEFFICIENTS*			*FUEL-COST COEFFICIENTS WITH VPE*	
			a_i (\$)	$b_i(\$/MW)$	$c_i(\$/MW^2)$	e_i	f_i
1	0	680	0.00028	8.10	550	300	0.035
2	0	360	0.00056	8.10	309	200	0.042
3	0	360	0.00056	8.10	307	200	0.042
4	60	180	0.00324	7.74	240	150	0.063
5	60	180	0.00324	7.74	240	150	0.063
6	60	180	0.00324	7.74	240	150	0.063
7	60	180	0.00324	7.74	240	150	0.063
8	60	180	0.00324	7.74	240	150	0.063
9	60	180	0.00324	7.74	240	150	0.063
10	40	120	0.00284	8.6	126	100	0.084
11	40	120	0.00284	8.6	126	100	0.084
12	55	120	0.00284	8.6	126	100	0.084
13	55	120	0.00284	8.6	126	100	0.084

This case study consisted of 13 thermal units of generation with the effects of valve-point loading compared to other approaches optimization, Furthermore, the low standard deviation value indicated a good convergence of AGSK method in the 20 runs it has been given more stability and low cost within others techniques As indicated in **"Table 6".**

Table 6 : Comparaison of results in the 13-unit system.

Techniques	Minimum	Average	Maximum	Std.dev
TLBO[12]	18141.6	NA	NA	NA
NN-EPSO[12]	18442.59	NA	NA	NA
C-GRASP[13]	18394.07	18550.105	18699.339	65.7290
SA[13]	18950.174	19393.114	19782.516	181.9200
MFEP[14]	122647.57	123489.74	124365.47	NA
CEP[15]	18048.21	18190.32	18404.04	NA
PSO[15]	18030.72	18205.78	NA	NA
CGA[15]	18671.64	18791.31	18935.83	NA
DEC-SQP[16]	18172.20	18301.08	18440.74	95.2699
MSL[29]	18158.68	NA	NA	NA
AGSK	**18022.190**	**18107.64**	**18198.34**	**62.0000**

Table 7 : the system units power in case 2.

Power output (MW)	TLBO[12]	NN-EPSO[12]	MSL[29]	AGSK
Pg 1	448.80	490.00	628.3	**448.80**
Pg 2	224.60	189.00	310.85	**224.40**
Pg 3	149.61	214.00	310.85	**152.93**
Pg 4	109.87	160.00	60	**109.87**
Pg 5	109.87	90.00	60	**109.87**
Pg 6	109.89	120.00	60	**109.87**
Pg 7	109.86	103.00	60	**109.87**
Pg 8	109.90	88.00	60	**109.87**
Pg 9	109.90	104.00	60	**159.73**
Pg 10	77.40	13.00	40	**77.40**
Pg 11	77.40	58.00	40	**77.40**
Pg 12	92.42	66.00	55	**55.00**
Pg 13	70.49	55.00	55	**55.00**
Total power (MW)	1800	1800	1800	**1800**
PLoss(MW)	115	442.590	158.680	**22.190**
Minimum cost ($/h)	18115.000	18442.590	18158.680	**18022.190**

The optimal generation scheduling of all 13 generators obtained by the proposed AGSK for 18022,190 $ compared to TLBO for 18115 $ and MSL for 18158,680 $ approach along with those obtained by other optimization techniques as mention above on **"Table 6"**, Considering VPL the AGSK has got the best results among others techniques in terms of all indices that has been already compared to.

Figure 13 **&** **Figure 14** **&** **Figure 15** Show all ASGK obtained constraints results.

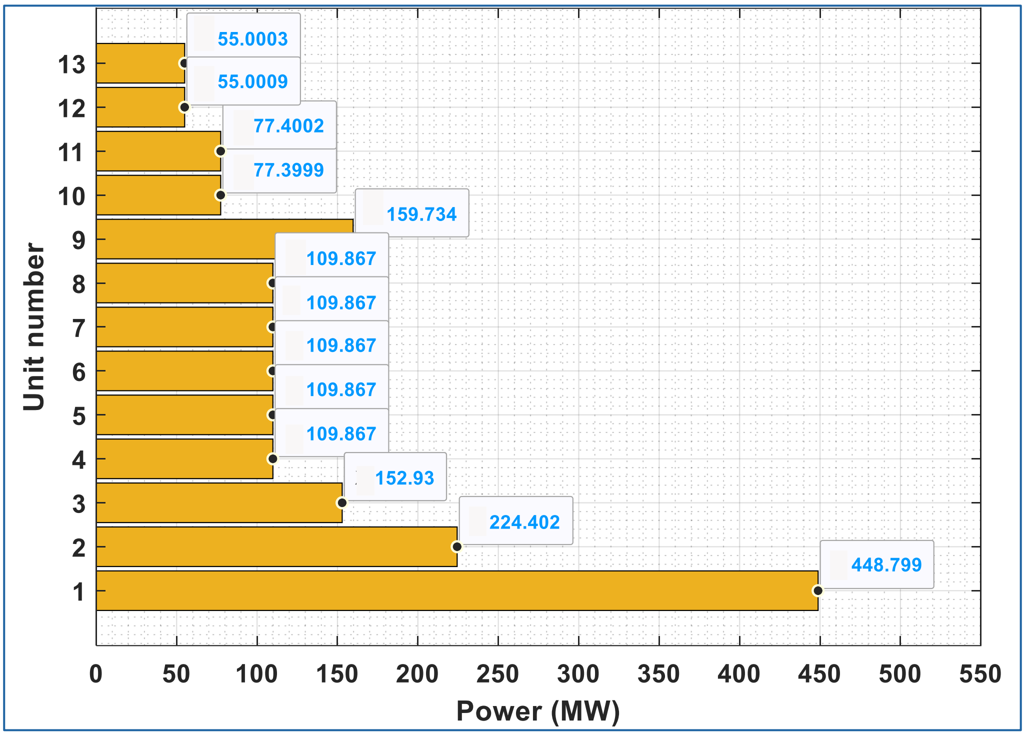

Figure 13 : power genereated from each unit for system 2.

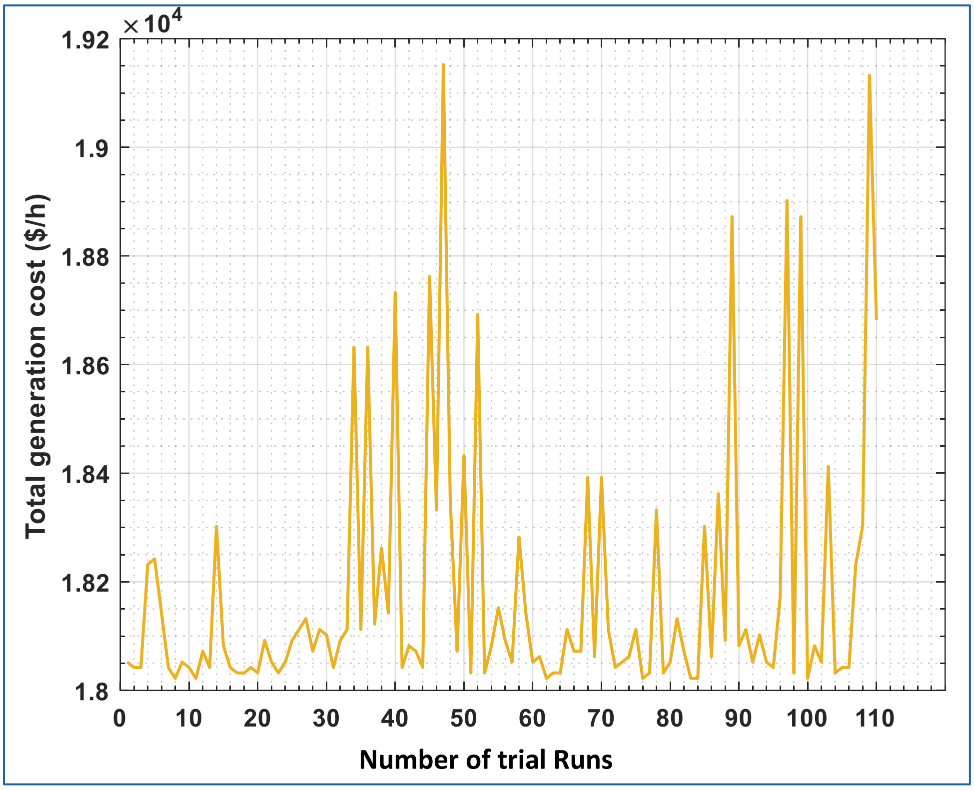

Figure 14 : dissemination of fuel costs of the AGSK technique for system 2.

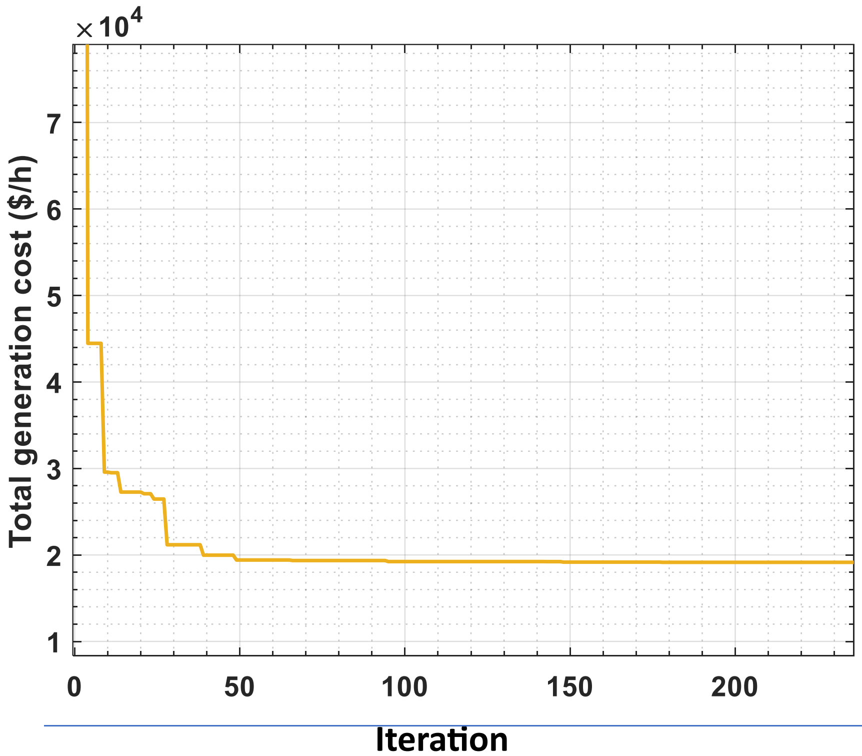

Figure 15 : convergence characteristic of the AGSK for system 2.

III.3.3 Test system 3

This system consists of 40 units with VPL effects. The system data are adopted from [25], For this test system, the transmission loss not taken despite a power demand of 10500 MW, the system data are below in **"Table 8"**. The obtained results by the proposed AGSK technique with the other state-of-the-art optimization techniques are showed on **"Table 9"**.

Table 8 : data system for 40-unit with valve-point loading.

Unit	P_i^{Min}	P_i^{Max}	*FUEL-COST COEFFICIENTS*			*FUEL-COST COEFFICIENTS WITH VPE*	
			a_i ($)	$b_i(\$/MW)$	$c_i(\$/MW^2)$	e_i	f_i
1	36	114	0.0069	6.7	94.705	100	0.08
2	36	114	0.0069	6.7	94.705	100	0.08
3	60	120	0.02028	7.1	309.54	100	0.08
4	80	190	0.00942	8.2	369.03	150	0.06
5	47	97	0.0114	5.4	148.89	120	0.08
6	68	140	0.01142	8.1	222.33	100	0.08
7	110	300	0.00357	8	287.71	200	0.04
8	135	300	0.00492	7	391.98	200	0.04
9	135	300	0.00573	6.6	455.76	200	0.04
10	130	300	0.00605	13	722.82	200	0.04
11	94	375	0.00515	13	635.2	200	0.04
12	94	375	0.00569	13	654.69	200	0.04
13	125	500	0.00421	13	913.4	300	0.04
14	125	500	0.00752	8.8	1760.4	300	0.04
15	125	500	0.00708	9.2	1728.3	300	0.04
16	125	500	0.00708	9.2	1728.3	300	0.04
17	220	500	0.00313	8	647.85	300	0.04
18	220	500	0.00313	8	649.69	300	0.04
19	242	550	0.00313	8	647.83	300	0.04
20	242	550	0.00313	8	647.81	300	0.04
21	254	550	0.00298	6.6	785.96	300	0.04
22	254	550	0.00298	6.6	785.96	300	0.04
23	254	550	0.00284	6.7	794.53	300	0.04
24	254	550	0.00284	6.7	794.53	300	0.04

25	254	550	0.00277	7.1	801.32	300	0.04
26	254	550	0.00277	7.1	801.32	300	0.04
27	10	150	0.52124	3.3	1055.1	120	0.08
28	10	150	0.52124	3.3	1055.1	120	0.08
29	10	150	0.52124	3.3	1055.1	120	0.08
30	47	97	0.0114	5.4	148.89	120	0.08
31	60	190	0.0016	6.4	222.92	150	0.06
32	60	190	0.0016	6.4	222.92	150	0.06
33	60	190	0.0016	6.4	222.92	150	0.06
34	90	200	0.0001	9	107.87	200	0.04
35	90	200	0.0001	8.6	116.58	200	0.04
36	90	200	0.0001	8.6	116.58	200	0.04
37	25	110	0.0161	5.9	307.45	80	0.1
38	25	110	0.0161	5.9	307.45	80	0.1
39	25	110	0.0161	5.9	307.45	80	0.1
40	242	550	0.00313	8	647.83	300	0.04

This last case is considered for the aim to further demonstrate the effectiveness of the AGSK for large scale ELD problems in power systems, This test system consists of 40-generating units with valve point loading effects with no transmission losses for 10500MW, The results obtained by adopting the proposed AGSK algorithm are compared to those appeared in **"Table 9"** While considering the minimum of fuel cost average and maximum and also standard deviation and

Table 9 : Comparison of results in the 40-unit system.

Techniques	Minimum ($)	Average ($)	Maximum ($)	Std,dev
C-GRASP[13]	128883.2	130268.98	132839.22	972757
GA[13]	163402	163534.98	163623.34	640606
CEP[25]	123488.29	124793.48	126902.89	NA
FEP[25]	122679.71	124119.37	127245.59	NA
SCA[31]	122713.68	125235.13	130918.39	NA
CEP-PSO[30]	123670	124145.6	124900	NA
GAAPI[32]	125770.85	NA	NA	NA
SA[33]	122946.77	123180.7	124183.72	611900
PSO[34]	123323.97	123690.62	125103.28	NA
AGSK	**122652.8**	**123198**	**123948.2**	**504511**

Table 10 : Comparison of results in the 40-unit system.

Units	Power (MW)		
	PSO[34]	SA[33]	AGSK
Unit 1	113,116	112.410	**110.851**
Unit 2	113.010	110.730	**111.311**
Unit 3	119.702	119.980	**96.851**
Unit 4	89.847	144.620	**178.370**
Unit 5	95.062	94.680	**87.879**
Unit 6	139.209	68.810	**139.749**
Unit 7	299.927	261.450	**295.824**
Unit 8	287.491	285.580	**283.566**
Unit 9	292.316	297.050	**284.804**
Unit 10	292.273	130.210	**270.108**
Unit 11	169.766	94.330	**167.874**
Unit 12	94.344	95.570	**234.691**
Unit 13	216.871	304.610	**394.078**
Unit 14	304.790	485.580	**393.517**
Unit 15	304.563	326.720	**393.511**
Unit 16	304.302	303.420	**303.435**
Unit 17	489.173	491.020	**400.255**
Unit 18	491.336	489.120	**489.290**
Unit 19	510.880	513.500	**420.988**
Unit 20	511.474	508.880	**509.263**
Unit 21	524.814	524.690	**521.752**
Unit 22	524.775	529.880	**523.502**
Unit 23	525.563	529.350	**524.021**
Unit 24	522.712	524.390	**522.582**
Unit 25	503.211	526.840	**522.458**
Unit 26	524.199	517.790	**433.293**
Unit 27	10.082	10.020	**11.526**

Unit 28	10.663	10.050	**11.759**
Unit 29	10.418	10.050	**12.683**
Unit 30	94.244	96.060	**89.152**
Unit 31	190.377	189.160	**160.298**
Unit 32	189.796	189.410	**167.494**
Unit 33	189.813	172.230	**161.835**
Unit 34	199.797	199.200	**164.024**
Unit 35	199.284	198.420	**164.354**
Unit 36	199.165	199.550	**164.627**
Unit 37	109.291	109.930	**89.733**
Unit 38	109.087	90.480	**90.996**
Unit 39	109.909	109.930	**87.913**
Unit 40	513.348	524.300	**509.782**
Minimum Cost ($)	123323.97	122946.77	**122652.80**
Total Power (MW)	10500	10500	**10500**

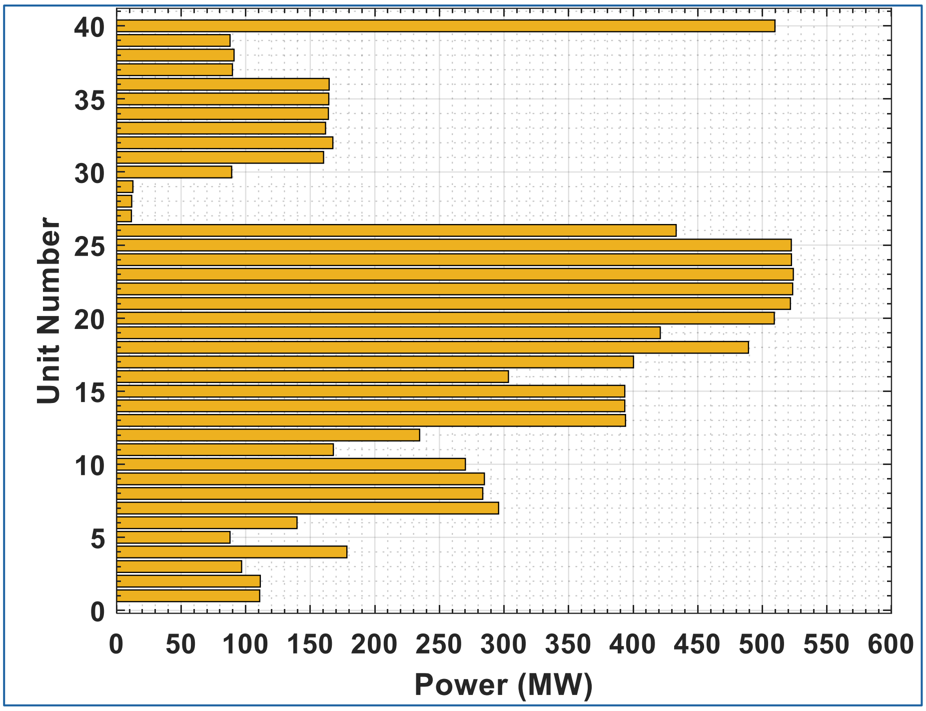

Figure 16 : power genereated from each unit for system 3.

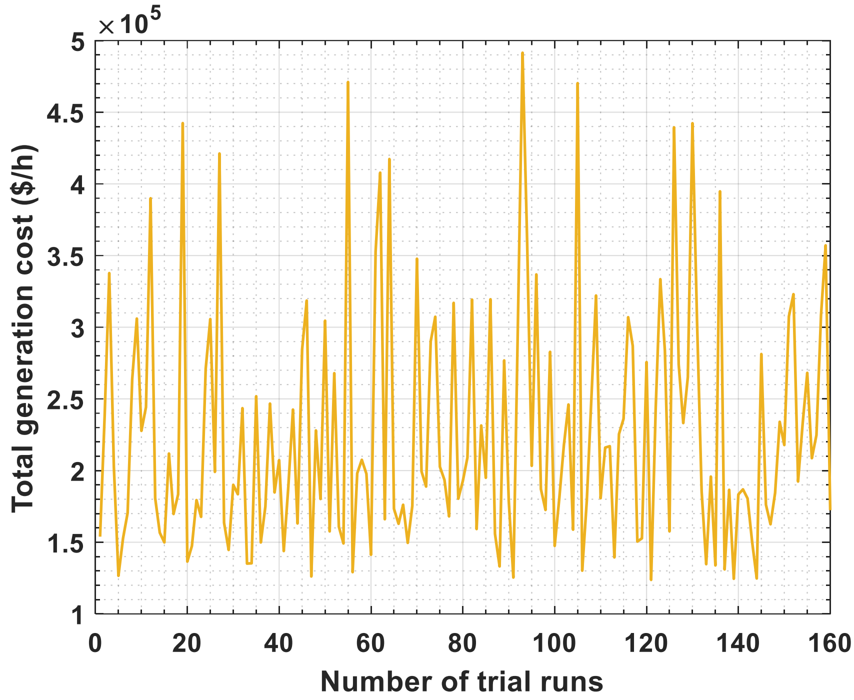

Figure 17 : dissemination of fuel costs of the AGSK technique for system 3.

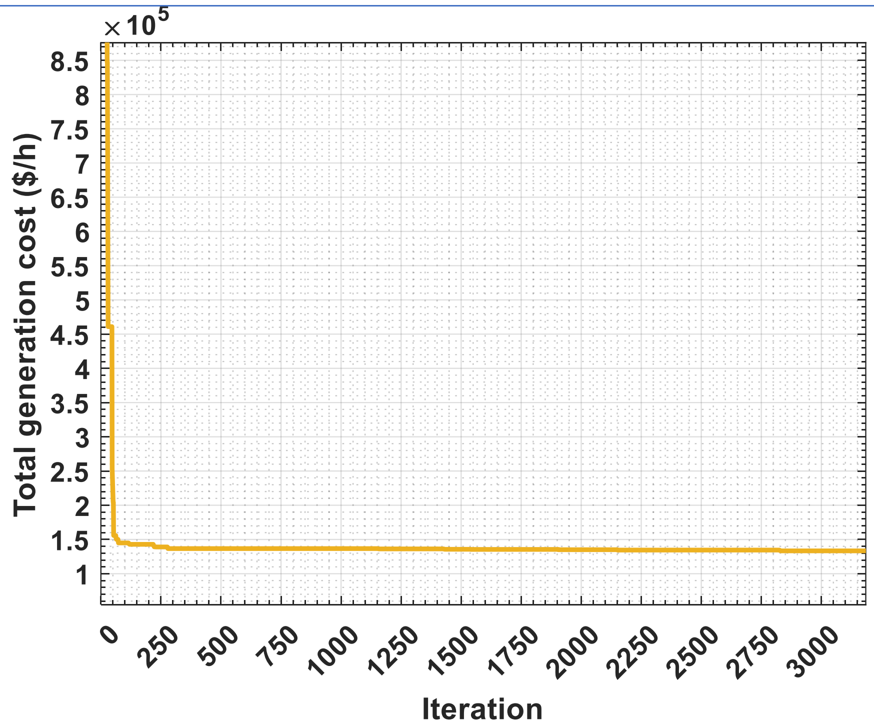

Figure 18 : convergence characteristic of the AGSK for system 3.

Figure 16 : power genereated from each unit for system 3., **Figure 17 :** dissemination of fuel costs of the AGSK technique for system 3., **Figure 18 :** convergence characteristic of the AGSK for system 3.

In **Table 9 :** Comparison of results in the 40-unit system." results obtained from the AGSK are for a power demand of 10,500 MW and VPE, In the literature, the optimization outcomes are contrasted to other optimization techniques. It is observed that in order to reduce the unit's fuel costs which start with best minimum cost for AGSK **122652,80 $**, then FEP 122679,71 $ & SCA 122713,68 $, and also AGSK has the lowest standard deviation among others techniques , with such as characteristic for minimum cost that's give the AGSK the best effect to solve this system case with the correspondent constraints.

III.3.4 Test system 4

This test system consists of 10 generating units with VPL effect and has a power demand of 2000 MW, consisting a non-smooth fuel cost and emission level functions, Unit data in **"Table 12"** & **" Table 13 "** and loss coefficients have been given.

Table 12 : data system of fuel for 10 unit with valve-point loading.

Unit	P_i^{Min}	P_i^{Max}	a_i ($/h)	b_i ($/MWh)	c_i ($/MW^2h$)	e_i ($/h)	f_i (rad/MW)
1	10	55	0.1295	40.5407	1000.403	33	0.0174
2	20	80	0.1091	39.5804	950.606	25	0.0178
3	47	120	0.1251	36.5104	900.705	32	0.0162
4	20	130	0.1211	39.5104	800.705	30	0.0168
5	50	160	0.1525	38.5390	756.799	30	0.0148
6	70	240	0.1059	46.1592	451.325	20	0.0163
7	60	300	0.0355	38.3055	1243.531	20	0.0152
8	70	340	0.0280	40.3965	1049.998	30	0.0128
9	135	470	0.0211	36.3278	1658.569	60	0.0136
10	150	470	0.0180	38.2704	1356.659	40	0.0141

Table 13 : data system of emission for 10 unit.

Unit	$\alpha_i\,(ib/h)$	$\beta_i(ib/MWh)$	$\delta_i(ib/MW^2h)$	$\eta_i(ib/h)$	$\gamma_i(1/MW)$
1	4.702	-398.64	36000.12	0.25475	0.01234
2	4.652	-395.24	35000.56	0.25475	0.01234
3	4.652	-390.23	33000.56	0.25163	0.01215
4	4.652	-390.23	33000.56	0.25163	0.01215
5	0.420	32.77	1385.93	0.24970	0.01200
6	0.420	32.77	1385.93	0.24970	0.01200
7	0.680	-54.55	4026.69	0.24800	0.01290
8	0.680	-54.55	4026.69	0.24990	0.01203
9	0.460	-51.12	4289.55	0.25470	0.01234
10	0.460	-51.12	4289.55	0.25470	0.01234

transmission loss coefficients for 10 Units .

$$\boldsymbol{B_{ij}} = \mathbf{10^{-4}} \times \begin{bmatrix} \mathbf{0.49} & \mathbf{0.14} & \mathbf{0.15} & \mathbf{0.15} & \mathbf{0.16} & \mathbf{0.17} & \mathbf{0.17} & \mathbf{0.18} & \mathbf{0.19} & \mathbf{0.20} \\ \mathbf{0.14} & \mathbf{0.45} & \mathbf{0.16} & \mathbf{0.16} & \mathbf{0.17} & \mathbf{0.15} & \mathbf{0.15} & \mathbf{0.16} & \mathbf{0.18} & \mathbf{0.18} \\ \mathbf{0.15} & \mathbf{0.16} & \mathbf{0.39} & \mathbf{0.10} & \mathbf{0.12} & \mathbf{0.12} & \mathbf{0.14} & \mathbf{0.14} & \mathbf{0.16} & \mathbf{0.16} \\ \mathbf{0.15} & \mathbf{0.16} & \mathbf{0.10} & \mathbf{0.40} & \mathbf{0.14} & \mathbf{0.10} & \mathbf{0.11} & \mathbf{0.12} & \mathbf{0.14} & \mathbf{0.15} \\ \mathbf{0.16} & \mathbf{0.17} & \mathbf{0.12} & \mathbf{0.14} & \mathbf{0.35} & \mathbf{0.11} & \mathbf{0.13} & \mathbf{0.13} & \mathbf{0.15} & \mathbf{0.16} \\ \mathbf{0.17} & \mathbf{0.15} & \mathbf{0.12} & \mathbf{0.10} & \mathbf{0.11} & \mathbf{0.36} & \mathbf{0.12} & \mathbf{0.12} & \mathbf{0.14} & \mathbf{0.15} \\ \mathbf{0.17} & \mathbf{0.15} & \mathbf{0.14} & \mathbf{0.11} & \mathbf{0.13} & \mathbf{0.12} & \mathbf{0.38} & \mathbf{0.16} & \mathbf{0.16} & \mathbf{0.18} \\ \mathbf{0.18} & \mathbf{0.16} & \mathbf{0.14} & \mathbf{0.12} & \mathbf{0.13} & \mathbf{0.12} & \mathbf{0.16} & \mathbf{0.40} & \mathbf{0.15} & \mathbf{0.16} \\ \mathbf{0.19} & \mathbf{0.18} & \mathbf{0.16} & \mathbf{0.14} & \mathbf{0.15} & \mathbf{0.14} & \mathbf{0.16} & \mathbf{0.15} & \mathbf{0.42} & \mathbf{0.19} \\ \mathbf{0.20} & \mathbf{0.18} & \mathbf{0.16} & \mathbf{0.15} & \mathbf{0.16} & \mathbf{0.15} & \mathbf{0.18} & \mathbf{0.16} & \mathbf{0.19} & \mathbf{0.44} \end{bmatrix}$$

This case study examines ten generation units with respect to the valve-point effect. The cost of petroleum and emission factors, The generation outputs of the most appropriate solutions for ELD, ECD problem for 2000 MW, A comparison between the ELD solutions discovered by AGSK and other algorithms in **"Table 14"**

Table 14 : solutions by AGSK and others techniques for system 4 ELD.

Unit	ELD		
	AGSK	DE[35]	CIHSA[36]
pg1	55	55.0000	55
pg2	80	79.8063	80
pg3	106.9055	106.8253	106.93473
pg4	100.5794	102.8307	100.60032
pg5	81.4990	82.2418	81.47679
pg6	83.0548	80.4352	83.02687
pg7	300	300.0000	300
pg8	340	340.0000	340
pg9	470	470.0000	470
pg10	470	469.8975	470
Total Load (MW)	2087.038	2087.037	2087.039
Power (MW)	2000	2000	2000
Power Loss(MW)	87.03831	87.03680	87.03871
Fuel Cost ($/h)	**111497.629**	111500	111497.631
Emission (Lb/h)	5687.088	4581	4572.2763
Total Cost ($/h)	/	/	/

"Table 15" shows the solutions of ECD problem for 2000 MW load demand using AGSK and other algorithms. According to this table, the best emission found by proposed algorithm and other techniques.

Table 15 : solutions by AGSK and others techniques for system 4 ECD.

Unit	ECD		
	AGSK	DE[35]	CIHSA[36]
pg1	55.0000	55	55.000
pg2	80.0000	80	80.000
pg3	106.9055	80.5924	81.150
pg4	100.5794	81.0233	81.360
pg5	81.4990	160	160.000
pg6	83.0548	240	240.000
pg7	299.9999	292.7434	294.508
pg8	339.9999	299.1214	297.269
pg9	470.0000	394.5147	396.720
pg10	470.0000	398.6383	395.588
Total Load (MW)	2087.038	2081.634	2081.595
Power (MW)	2000	2000	2000
Power Loss(MW)	87.03831	81.63350	81.59465
Fuel Cost ($/h)	144946.903	111640	116412.5655
Emission (Lb)	**3832.487**	3923.400	3932.243
Total Cost ($/h)	/	/	/

A comparison between the solutions found by AGSK and the results obtained by other algorithms for ELD and ECD is provided in **Table 14** for ELD & for ECD **"Table 15"**, According to the previous tables, the AGSK method achieves the lowest minimum fuel cost in ELD for **111497.629 $** Compared to 111500 $ for DE [35] and 111497.631 $ for CIHSA [36] , and the most minimal emission level in ECD is for AGSK by **3832.487 lb** which is the best among others emission such as DE [35] how has 3923.400 lb and CIHSA [36] for 3932.243 lb, its obvious that the AGSK Algorithm achieved the best results for the 2 types of the system case on Power Load Dispatching total cost and Emission which prove the efficiency and robustness of the proposed AGSK among the other optimization.

General Conclusion

In this paper, a newly developed metaheuristic Adaptive Gaing Sharing Knowledge (AGSK) algorithm is presented and used to solve the multiobjective environmental/economic dispatch problem in the presence of generators with nonsmooth and nonconvex fuel cost functions. AGSK, which is one of the recent heuristic algorithms improved from the original GSK by Ali Wagdy Mahmoud for solving optimization problems, has a number of benefits, such as its few control variables, local searching capability, quick results, simple structure, and easy application.

For the purpose of demonstrating the application of the proposed algorithm, it has been investigated and tested on four distinct test systems. First, six generators with quadratic cost functions and economic load dispatch problems are utilized to test AGSK. The proposed algorithm is then applied to 13 generators with a nonsmooth cost function and valve point effect, followed by 40 units with VPE. And lastly, a system with ten units for ELD and ECD The implementation results of this proposed algorithm demonstrated the efficacy of the AGSK in resolving the ELD and ECD problems on various test systems.

In addition, the results of the proposed algorithm have been compared to those of the techniques described in the literature, demonstrating that the proposed method confirms an effective, high-quality solution for CEED problems. Nevertheless, based on the simulation results, it appears that the appropriate selection of the knowledge factor and run numbers and setting a high value for Maxnfes are of the highest priority for the algorithm's convergence. Since AGSK is a relatively new algorithm, it should be extended to include more objective functions or constraints for more realistic problems, as well as other data sets and standard test problems. In addition, future studies comparing the current metaheuristic algorithm to other methodologies are required to determine its strengths and limitations.

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