UNIVERSITE KASDI MERBAH OUARGLA
Faculté des Sciences Appliquées
Département de Génie Electrique

Mémoire

MASTER ACADEMIQUE

Domaine : Sciences et technologies

Filière : Electrotechnique

Spécialité : Réseaux électriques

Présenté par :

Benrezigue abdelkader Nadjmaoui abdelatif

Thèse :

Gaining-sharing knowledge based algorithm for solving economic Load dispatch and emission

Soumis au jury composé de :

Mr Bouhadouza Boubekeur	MAA	Président	UKM Ouargla
Mr Benyekhlef Larouci	MCB	Encadreur/rapporteur	UKM Ouargla
Mr Boudjella Houari	MCB	Examinateur	UKM Ouargla

Année universitaire 2022 / 2023

بسم الله الرحمن الرحيم

Acknowledgements

Thank Allah that we have agreed to complete this humble work Then all thanks and respect to the esteemed ***Dr. Benyekhlef Larouci*** *for framing and guiding us We also thank the jury members and do not forget about our former professors since we joined the University We thank everyone who contributed to this work, even with a kind word.*

DEDICATION

To the dearest people and bring them closer to my heart, to my dear mother, may Allah prolong her life.To those who supported me and took my steps with me. I was pleased with the difficulties to my dear wife, who endured a lot and suffered. And my standing in this place would not have happened without her constant encouragement to me.

To my flowers and my liver.Dear children (Younes, Mohamed Riadh and Inas), And all my family. Who have been deprived of me for the entire period that I have spent preparing this memorandum .

To all my teachers and co-workers .

☆ BENREZIGUE☆

DEDICATION

To the author of a fragrant biography, and an enlightened thought; he was credited with the first achievement of higher education for me (my beloved father), Allah prolonged his life. To the one who put me on the path of life, made me calm, and took care of me until I became big (Dear Mom). To my brothers, who have had a great impact on many obstacles and difficulties. To all my esteemed teachers, who have not hesitated to extend a helping hand to me, I dedicate this research to you

⭐NADJMAOUI⭐

Abstract
The knowledge-based algorithms leverage the acquired knowledge to optimize the power dispatch problem. Various optimization techniques, such as linear programming, genetic algorithms, and particle swarm optimization, are employed to determine the optimal generation levels for different power plants. These algorithms consider multiple objective functions, including fuel costs, emission levels, and system reliability, while respecting operational constraints such as generation limits, transmission losses, and reserve requirements.

Résumé :
Les algorithmes basés sur la connaissance exploitent les connaissances acquises pour optimiser le problème de répartition de l'énergie. Diverses techniques d'optimisation, telles que la programmation linéaire, les algorithmes génétiques et l'optimisation des essaims de particules, sont utilisées pour déterminer les niveaux de production optimaux pour différentes centrales électriques. Ces algorithmes prennent en compte de multiples fonctions objectives, notamment les coûts du carburant, les niveaux d'émission et la fiabilité du système, tout en respectant les contraintes opérationnelles telles que les limites de production, les pertes de transmission et les réserves requises.

ملخص:
تستغل الخوارزميات القائمة على المعرفة المكتسبة لتحسين مشكلة توزيع الطاقة. تستخدم تقنيات التحسين المختلفة، مثل البرمجة الخطية والخوارزميات الجينية وتحسين سرب الجسيمات، لتحديد مستويات الإنتاج المثلى لمحطات الطاقة المختلفة. تأخذ هذه الخوارزميات في الاعتبار وظائف موضوعية متعددة، بما في ذلك تكاليف الوقود ومستويات الانبعاثات وموثوقية النظام، مع احترام القيود التشغيلية مثل حدود الإنتاج وخسائر النقل والاحتياطيات .

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List of Symbols and Acronyms

Symbols

N_g **:**is the number of operating generators

a_i**,**b_i **, and** c_i **:** are cost coefficients of the i-th generator

e_i **and** f_i **:** are valve-point effects coefficients of the i-th generator

P_T **:** the total power demand in MW

P_L **:** represents the transmission losses

B_{ij} **,** B_{0i} **and** B_{00} **:** are the loss coefficients

P_{min} **:** the minimum active power limit of each generator

P_{max} **:** he maximum active power limit of each generator

$p_j^{(t-1)}$ **:** is the output power

j^{th} **:** unit in MW respectively

Pz_i **:** the number of prohibited operating zones

F: indicates the single objective to be minimized

$C_{i,t}(P_{i,t})$**:** the fuel cost of Ng generators

$E_{i,t}(P_{i,t})$ **:** the emissions generated

f_i **:** the fuel cost coefficients of the i^{th} generator due to VPE

α_i , β_i , γ_i , η_i **,and** δ_i **:** are the emission curve coefficients.

B_{ij} **:** the transmission loss coefficients

P_i^{min} **and** P_i^{max} **:** he minimum and the maximum power limits of $P_{i,t}$

T_{jref}**:** the reference temperature of the panels at 25°C

T_j **:** the cells junction temperature (°C)

C_e**:** the efficiency factor

P_{RES} **:** the output power of the renewable energy resource

r: the interest scale and N is the investment duration in years

$rand_k$: denotes uniformly distributed random number in the range 0 and

$\boldsymbol{Dimj}$ **and** $\boldsymbol{Dims}$ **:** represent the dimension for the junior and senior stage respectively.

$\boldsymbol{Gen^{max}}$ **:** the maximum count of generations and G is the count of generation

$\boldsymbol{\omega_{ps}}$**:** the sum of the differences between old fitness value and the new fitness value

$\boldsymbol{x_i^{old}}$ **:** the new solution

$\boldsymbol{x_i^{new}}$ is the old solution

NFE: the current number of functions evals

$\boldsymbol{MAX_{NFT}}$ **:** the max allowable number of functions evals

$\boldsymbol{P_{i,k}^{L}}$ **and** $\boldsymbol{P_{i,k}^{U}}$ **:** the lower bound and upper bound of the k-th prohibited zone of the i-th generator

Acronyms

EPD: economic power dispatch.

ED: economic dispatch.

TL: transmission losses.

POZ: Prohibited Operating Zones.

DCEED: Dynamic Combined economic environmental dispatch

DED: Dynamic economic dispatch.

DEnD: Dynamic environmental dispatch

AC : Annuitization coefficient

.**ELD:** Economic Load Dispatch

EED: Economic emission dispatch.

GSK: Gaining–Sharing Knowledge

VEGA: vector evaluated genetic algorithm

NDSA: non-dominated sorting algorithm

MOGA : multi-objective genetic algorithm

SPEA2 : improved strength pareto evolutionary algorithm

NP : Number of population size

APGSK : Adaptation of parameters Gaining–Sharing Knowledge

NLPSR : Non-Linear Population Size Reduction

Genaral Introduction

- **Problem**

Energy and heat are the basics of daily life. But the problem lies in how to exploit this energy as much as possible from its generation to its distribution until its exploitation, and that is proportional to reducing costs in a direct proportion, in addition to this problem trying to reduce the emissions caused.

In this work, the problem of sending economic energy is considered by reducing the cost of fuel in electric power generation, to reduce emissions causing environmental pollution, we have prepared a definition about EPD, and ways to address it.

In turn, metaheuristic optimization techniques have become popular for finding the best solution to the problem, and the acquisition of knowledge sharing (GSK) offers a way to solve the EPD problem, including non-renewable and renewable energy sources (wind, solar).

- **Objective**

- Cost and emissions are combined to get the best possible solutions and the best results to reduce the cost of fuel and reduce emissions.

- The goal of this mathematical problem is to obtain a method for It is the development of a method that facilitates the acquisition and dissemination of knowledge among individuals or groups. While this is usually a broader concept that extends beyond mathematical problems, we can explore how mathematical techniques and methods can contribute to the knowledge acquisition process.

- The solutions of our approach that we will study by that algorithm are compared with the results available in the literature. We are trying to improve the performance of the proposal method in saving fuel costs and reducing emission levels compared to current methods.

Chapter I:

Economic load Dispatch (ELD)

I.1 Introduction :

The EPD is a principal and integral part of the feeding system and is integrated under the duration of the economic operation of the feeding system. The purpose of EPD is to determine the power outputs for the production units in order to cover the load demand, according to the minimum fuel cost for each production group and meet the different operating constraints over a finished shipping period [1].

The EPD problem has been solved via many traditional techniques such as linear programming, nonlinear programming, quadratic programming, Newton-based techniques, and inland point methods. Usually these methods are based on the assumption that the fuel cost characteristic of the generating unit is a smooth and convex function. However, there are cases when it is not possible or appropriate to represent the fuel cost property of a unit as a convex function for example. Hence access to the true global optimization of the problem is not easily accessible. Then new numerical methods are needed to deal with these difficulties especially those that have maximum high-speed research and are not trapped at the local minimum [2].

The purpose of the economic dispatch is to schedule the outputs of all available generation units in the power system such that the fuel cost is minimized while system constraints are satisfied. Also it can be explained as the process of allocating generation among the committed units such that the constraints imposed are satisfied and the energy requirements are minimized. Furthermore, the economic power dispatch for interconnected power system can be explained as the process of finding the total real and reactive power schedule of each power plant in such a way as to minimize the operating cost. This means that the generator's real and reactive power is allowed to vary within certain limits so that it can meet the demand with minimum fuel cost. This is called the optimal power flow. The optimal power flow is used to optimize the power flow solution of large scale power system. This is done by minimizing selected objective functions while maintaining an acceptable system performance in terms of generators capability limits and the output of the compensating devices. It is useful to divide economic dispatch practices in two separate stages: unit commitment and unit dispatch. Unit commitment takes place before real-time operation and determines the set of generating units that will be available for dispatch. Unit dispatch occurs in real time and determines the amount of generation needed from each available unit.

The Main objective of the power economic dispatch is to find the total power generation output so as to minimize operating cost. Beside the main objective, there are also numbers of objectives listed as follows:

- To schedule the committed generating units outputs so as to meet the required load demand at minimum operating cost while satisfying all units and system equality and inequality constraints.
- Minimization of the emissions (the gaseous emission such as SO2, NOx, CO and CO2 produced by thermal power plants).
- Maximization of the profit by reducing the total cost.
- Maintain System Stability and Security Constraint. [9].

I.2 Problem Formulation

I.2.1 Objective Function.

The mathematical model of ED can be formulated as follows :

$$\min\ C(P) = \sum_{i=1}^{N} F_i(P_i), \quad P=\left[P_1, P_2, \dots, P_{N_S}\right] \in R^{N_S}$$
$$\text{s.t } h_j(P) = 0\ , \quad j = 1,2,\dots,m \tag{I.1}$$
$$g_j(P) \leq 0\ , \quad j = 1,2,\dots,q$$

where C(P) is the total generation cost (in \$/h), $N_g$is the number of operating generators, i is the active power output of the i-th generator (in MW), $i = 1,2,\dots,N_g$, $F_i(Pi)$ is the generation cost function of the i-th generator (in \$/h), $i = 1,2,\dots,N_g$,m and q are the number of equality constraints and inequality constraints, respectively, $h_j(P)$ is the j-th equality constraint $j = 1,2,\dots,m$, and $g_j(P)$ is the j-th inequality constraint $j = 1,2,\dots,q$

The objective function of traditional ED problem is approximately formulated as follows:

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

where a_i,b_i , and c_i are cost coefficients of the i-th generator.

In practice ,modelling valve-point effects is necessary and can be formulated as follows :

$$F_i(\mathrm{P_i}) = \mathrm{a_i} + \mathrm{b_i P_i} + \mathrm{c_i P_i^2} + |e_i.\sin\left(f_i \times \left(P_{i,min} - P_i\right)\right)| \tag{I.3}$$

Where e_i and f_i are valve-point effects coefficients of the i-th generator and i,min is the minimum active power generation limit of the i-th generator (in MW).[4]

I.3 Equality and Inequality Constraints

I.3.1 Equality Constraint

In order to the power balance, the total generated power should meet the power demand and transmission losses (TL).

$$\sum_{i=1}^{N_g} P_i = P_T + P_L \tag{I. 4}$$

Where P_T is the total power demand in MW, and P_L represents the transmission losses in MW which can be computed by using B-coefficients and is given by :

$$P_L = \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} P_i B_{ij} P_j + \sum_{i=1}^{N_g} B_{0i} P_i + B_{00} \tag{I. 5}$$

where B_{ij} , B_{0i} and B_{00} are the loss coefficients which are constant under normal operational conditions.[6].

I.3.2 Inequality constraints:

The generator's powers loading must not exceed a certain thermal limit. The thermal constraint restricts the maximum active power generation so that rise in temperature remains within limits.

$$P_{min} \leq P \leq P_{max} \quad (I.6)$$

where: P_{min} is the minimum active power limit of each generator, P is the active power output of each generator and P_{max} is the maximum active power limit of each generator. [8].

I.3.3 Prohibited Operating Zones Constraints [4]:

Generators should avoid operating in prohibited zones (POZ):

$$\begin{cases} P_{i,min} \leq P_i \leq P_{i,1}^L \\ P_{i,k-1}^U \leq P_i \leq P_{i,k}^L, & k = 2,3, \dots, Pz_i \\ P_{i,Pz_i}^U \leq P_i \leq P_{i,mqx} \end{cases} \quad (I.7)$$

where $Pz_i$is the number of prohibited operating zones of the i-th generator and $P_{i,k}^L$and are$P_{i,k}^U$ the lower bound and upper bound of the k-th prohibited zone of the i-th generator, respectively. [4].

I.4. DCEED Problem Formulation Including VPE:

Due to the dynamic behavior of the electrical network and the prodigious variations in load demand on the consumer side, the DCEED problem can be described as a multiobjective mathematical optimization problem, which is non-linear and dynamic. DCEED is a constraint optimization problem that minimizes simultaneously the fuel cost and emission effects in order to meet a power system's load demand over some appropriate periods while meeting certain equality and inequality constraints .

.I 4.1. Objective Function :

DCEELDP's objective is to minimize total fuel costs while also reducing the level of emissions emitted by generating units. Thus, the objective function is mathematically defined as the weighted summation of the production cost of generating units and emissions caused by fossil fuel thermal plants, which is shown below :

$$\text{minF} = \sum_{t=1}^{T} \sum_{i=1}^{N_g} C_{i,t}(P_{i,t}) + \text{pp}f_i \sum_{t=1}^{T} \sum_{i=1}^{N_g} E_{i,t}(P_{i,t}) \quad (I.8)$$

Where F indicates the single objective to be minimized; $C_{i,t}(P_{i,t})$ denotes the fuel cost of Ng generators in the tth (t =1, 2, . . . , T) time interval in USD/h; $E_{i,t}(P_{i,t})$ stands for the emissions generated by the generation stations over T dispatch intervals in kg/h; $P_{i,t}$ denotes the dynamic dispatch power in MW. ppf_i is the price penalty factor determined by the ratio of $C_i(P^{max})$ and $E_i(P^{min})$ in USD/kg.

I.4.1.1. Dynamic Economic Load Dispatch Model (DED)

The objective of the DED problem is to minimize the overall economic cost of fossil fuel during a 24-h period. In some large generators, their cost functions are also non-linear, due to the effect of the valve opening . Consequently, the valve dynamics increase several local minimum points in the cost function, hence complicating the problem. The DED problem involved with VPE is expressed as minimization of the production cost of power dispatch in the following way :

$$C_{i,t}(P_{i,t}) = \mathrm{a_i} + \mathrm{b_i P_{i,t}} + \mathrm{c_i P_{i,t}^2} + |e_i.\sin\left(f_i \times \left(P_i^{min} - P_i\right)\right)| \tag{I.9}$$

where $\mathrm{a_i}$, $\mathrm{b_i}$ and $\mathrm{c_i}$ are the coefficients of the fuel cost corresponding to the generator i; e_i, and f_i stand for the fuel cost coefficients of the i^{th} generator due to VPE ; and P^{min} denotes the minimum real power of the i^{th} (i = 1, 2, . . . , Ng) generating unit. 3.1.2.

I.4.1.2 Dynamic Environmental Dispatch Model (DEnD):

Global warming and increased movements to protect the environment have forced producers to reduce gas emissions caused by the combustion of fossil fuels in various power plants mainly due to sulfur dioxide (SO_2) and nitrate oxide (NOx) . Each thermal power plant will produce its power according to a dynamic non-smooth emission function given by the following quadratic form :

$$E_{i,t}(P_{i,t}) = \alpha_i + \beta_i P_{i,t} + \gamma_i P_{i,t}^2 + \eta_i \times exp\left(\delta_i P_{i,t}\right) \tag{I.10}$$

where α_i , β_i , γ_i , η_i , and δ_i are the emission curve coefficients.

I.4.2. Constraints Functions

The minimization of the DCEED problem is subject to the following constraints and limits:

I.4.2.1 Power Balance Constraint

The sum of total power generated by all generators at each time interval t should be matched with the load demand PD and the total transmission losses P_L in the corresponding time period, which is given as follows :

$$\sum_{i=1}^{N_g} P_{i,t} = P_{D,t} + P_{L,t} \qquad (I.11)$$

The power losses incurred in the transmission lines can be computed by using Kron's loss coefficients formula given below :

$$P_{L,t} = \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} P_{i,t} B_{ij} P_{j,t} \qquad (I.12)$$

where B_{ij} denotes the transmission loss coefficients. Wood et al.in provide detailed procedures for calculating the B coefficients.

I.4.2.2 Power Output Limits

The dispatch active power outputs of each generator must be between the capacities of each specific generating unit at each time interval :

$$P_i^{min} \le P_{i,t} \le P_i^{max} \qquad (I.13)$$

Where P_i^{min} and P_i^{max} indicate, respectively, the minimum and the maximum power limits of $P_{i,t}$ [3].

I.5. Problem formulation and optimization with the solar energy and wind energy:

I.5.1 Solar Energy :

The maximum power provided by a solar panel is given by the following characteristic:

$$P_s = P_1 . E_c . \left[1 + P_2 . \left(T_j - T_{jref}\right)\right] \qquad (I.14)$$

Ec is solar radiation, T_{jref} is the reference temperature of the panels at 25°C, T_j is the cells junction temperature (°C), P_1(MW) represent the characteristic dispersion of the panels and the value for one panel is included enters 0.095 to 0.105 and the parameter P_2 =0.47%/C°; is the drift in panels temperature.

The addition of one parameter P3 to the characteristic, gives more satisfactory results:

$$P_s = P_1 . \left[1 + P_2 . \left(T_j - T_{jref}\right)\right] . (P_3 + E_c) \qquad (I.15)$$

This simplified model makes it possible to determine the maximum power provided by a group of panels for solar radiation and panel temperature given, with only three constant parameters P_1(MW) , P_2(MW) and P_3(MW) and simple equation to apply. A thermal solar power station consists of a production of solar system of heat which feeds from the turbines in a thermal cycle of electricity production.

I.5.2 Wind energy:

The power contained in the form of kinetic energy, P (W), the wind is expressed by with:

$$P = \frac{1}{2}.\rho.C.A.v^3 \qquad (I.16)$$

A is the area traversed by the wind (m^2); ρ is the density of air (ρ = 1.225kg/m^3) and v is the wind speed (m / s).

The wind generator can recover some of this wind power and represents the power produced by wind generator:

$$P_{el} = \frac{1}{2}.\rho.C_e A.v^3.10^{-3} \qquad (I.17)$$

$C_e$is the efficiency factor, which depends on the wind speed and the wind generator architecture [5] .

I.5.3 Renewable Energy Integration :

Furthermore, both the fuel costs and the pollutants emission can be reduced by the inclusion of available renewable resources for the generation of power. The renewable energy resources are clean sources of energy which neither incurs any fuel cost nor does it emits harmful toxic gases in the atmosphere. Although these renewable energy sources do include some installation or maintenance cost whose cost function can be calculated as below:

$$F(P_{RES}) = P_{RES}\ (AC.I^P) + G^E\ ) \qquad (I.18)$$

whereP_{RES} is the output power of the renewable energy resources, AC is the annuitization coefficient, IP is the ratio of investment cost to established power in $/kW and GE is the operational and maintenance cost in $/kW. Annuitization coefficient can be calculated with the formula.

$$AC = \frac{r}{1-(1+r)^{-N}} \qquad (I.19)$$

where r is the interest scale and N is the investment duration in years.

This work on an islanded microgrid uses wind farms and photo voltaic (PV) system as the available RES for the minimization of fuel and emission costs and also to increase the efficiency and maintain an uninterrupted power supply. The operational and maintenance cost for the wind farm and PV system is 0.016$/kW invested at 9% interest scale for 20 years. The ratio of investment cost to establish power is 5000$/kW for PV system and 1400$/ kW for wind farm. So the cost function of PV becomes $F_{PV} = 547.7483 * P_{PV}$ and the cost function of wind is F_{WIND} = 153.3810 * P_{WIND}. Hence with the inclusion of RES the economic load dispatch function becomes :

$$ELD\ (P) = C_{i,t}(P_{i,t}) + 547.7483 * P_{PV} + 153.3810 * P_{WIND} \qquad (I.20)$$

And the inclusion of RES in the combined economic emission dispatch function, turns it into

$$ELD(P) = \sum_{t=1}^{T}\sum_{i=1}^{N_g} C_{i,t}(P_{i,t}) + \mathrm{pp}f_i \sum_{t=1}^{T}\sum_{i=1}^{N_g} E_{i,t}(P_{i,t}) + 547.7483 * P_{PV} + 153.3810 * P_{WIND} \qquad (I.21)$$

The above objective functions (I.24) and (I.25) are subject to constraints such as:

I.5.4 Generation constraints:

The power generated by the conventional generators as well as the RES must lie between a maximum and minimum limit. Mathematically**.**

$$P_{RES.min} \leq P_{RES} \leq P_{RES.max}$$
$$P_{RES.min} \leq P_{RES} \leq P_{RES.max} \quad (I.22)$$

I.5.5 Power supply-demand balance constraint:

The power generated at any instant of time by all the conventional generators and the RES should satisfy the total desired load of the system. This can be mathematically stated as:

$$P_{LOAD}=P_i+P_{RES}, \; i = 1,2,3\ldots\ldots g \quad (I.23)$$

This work focuses on minimizing (I.24) and (I.25) separately using various optimization techniques and a comparative study among the techniques as well as the minimized costs of ELD and EED.[7]

I.6 Conclusion

In this chapter we addressed the problem of sending economic emission power by reducing the cost of fuel in electrical power generation, and so on environmental pollution, we have prepared a definition about EPD, and ways to address it.

In contrast, metaheuristic optimization techniques have become common to find the best solution to the EED problem. Such algorithms include a colony optimizer, multi-verse optimizer, particle swarm optimization, gray wolf optimizer, biogeography-based optimization, enhanced exploratory whale optimization algorithm (EEWOA) , and hybrid bat–crow search algorithm (HBACSA); they are used exceptionally, in a unique, improved, or hybrid form with others approaches.

The next chapter proposes, presents Gaining-Sharing Knowledge(GSK) method for solving the DCEED problem, including VPE with and without renewable energy sources (wind and solar energy).

Chapter II:

Gaining–Sharing Knowledge (GSK)

II.1 Introduction :

Optimization techniques involve finding the best suitable values for decision variables that optimize the objective function. They are used in various fields of engineering to solve real-world problems. It has many applications in mechanics, economics, finance, machine learning, computer network engineering, etc. In real-world problems, it is difficult to find the exact or deterministic information of problems; therefore, randomness or uncertainty occurs. These problems come within the framework of stochastic programming, where the parameters of the problems are characterized by random variables that follow any probability distribution. Stochastic programming has many applications in various fields such as transportation, portfolio optimization, Supply Chain Management, electrical engineering, lot sizing and scheduling, water resource allocation, production planning, medical drug inventory etc. The basic idea of solving a stochastic programming problem is to transform probabilistic constraints into their equivalent deterministic constraints and then solve them using analytical or numerical methods. In this study, the problem of transfer with multi-objective functions and probabilistic constraints is considered [10]. The literature can be divided into three main directions: improving the current methods by controlling the parameters of the algorithms, hybridizing different algorithms to benefit from each one, and introducing a new algorithm [14]. The main goal of the problem is to reduce the transportation cost and total transportation time while meeting the demand requirements. Recently, a new algorithm inspired by nature has been introduced that is the acquisition of common knowledge, which is called GSK.

This algorithm is inspired by human age and the process of sharing and acquiring knowledge. To do this, GSK carries out two main stages, namely, the stages of acquiring knowledge from young and old. The problem is solved by the GSK algorithm, other metaheuristic algorithms and the solutions are compared to evaluate the relative performance of the algorithms. These algorithms are nature-inspired algorithms such as evolutionary algorithms inspired by natural evolution, swarm-based algorithms are based on the behavior of insects or animals, physics-based algorithms are inspired by the physical base and human-based algorithms are based on the philosophy of human activity [10].

II.2 Meta-heuristic:

II.2.1 Definition:

A metaheuristic is a high-level problem-independent algorithmic framework that provides a set of guidelines or strategies to develop heuristic optimization algorithms (Sörensen and Glover, To appear). Notable examples of metaheuristics include genetic/evolutionary algorithms, tabu search, simulated annealing, and ant colony optimization, although many more exist. A problem-specific implementation of a heuristic optimization algorithm according to the guidelines expressed in a metaheuristic framework is also referred to as a metaheuristic. The term was coined by Glover (1986) and combines the Greek prefix meta- (metá, beyond in the sense of high-level) with heuristic (from the Greek heuriskein or euriskein, to search). Metaheuristic algorithms, i.e., optimization methods designed according to the strategies laid out in a metaheuristic framework, are — as the name suggests — always heuristic in nature. This fact distinguishes them from exact methods, that do come with a proof that the optimal solution will be found in a finite (although often prohibitively large) amount of time. Metaheuristics are therefore developed specifically to find a solution that is “good enough” in a computing time that is “small enough”. As a result, they are not subject to combinatorial explosion – the phenomenon where the computing time required to find the optimal solution of NP-hard problems increases as an exponential function of the problem size. Metaheuristics have been demonstrated by the scientific community to be a viable, and often superior, alternative to more traditional (exact) methods of mixed integer optimization such as branch and bound and dynamic programming. Especially for complicated problems or large problem instances, metaheuristics are often able to offer a better trade-off between solution quality and computing time. Moreover, metaheuristics are more flexible than exact methods in two important ways. First, because metaheuristic frameworks are defined in general terms, metaheuristic algorithms can be adapted to fit the needs of most real-life optimization problems in terms of expected solution quality and allowed computing time, which can vary greatly across different problems and different situations. Secondly, metaheuristics do not put any demands on the formulation of the optimization problem (like requiring constraints or objective functions to be expressed as linear functions of the decision variables). However, this flexibility comes at the cost of requiring considerable problem-specific adaptation to achieve good performance [11].

II.2.2 Description of characteristics and optimization methods:

Optimization is a process that forms an integral part of daily life. In the most basic sense, it can be defined as a process of finding the best way to use available resources, while at the same time not violating any of the constraints that might exist. The optimization process involves several steps: define a system mathematically, identify its variables and the conditions they must satisfy, define properties of the system, and then seek the state of the system (that is, the values of the variables) that yields the most desirable properties, either maximum or minimum.

Throughout the years, several approaches have been proposed to carry out the optimization. Most of these approaches are based on classical methods, such as the Sequential Unconstrained Minimization Technique, the Augmented Lagrangian, Newton-Raphson, the Successive Quadratic Programming algorithm, the Steepest Descent Algorithm, Dynamic and Integer Programming, and the Stochastic Newton optimization method. Classical methods such as Linear Programming and Nonlinear Programming are efficient approaches that can be used to solve special cases of optimization problem in power system applications. However, a drawback of these techniques is that they are not well suited to solve complex optimization problems. As the complexities of the problem increase, especially with the introduction of uncertainties to the system, more complicated optimization techniques that overcome the limitations of classical approaches have to be used. Metaheuristic methods have been developed with this goal in mind.

Metaheuristic methods imitate the best features in nature, motivated by natural selection and social adaptation. Its fundamental properties and advantages have been described by many researchers:

- The basic concepts of metaheuristics can be described on an abstract level, unlinked to any specific problem. Metaheuristic algorithms range from simple local search procedures to complex learning processes.

- Metaheuristics use domain-specific knowledge in the form of heuristics that are controlled by an upper level strategy.
- Metaheuristics are strategies aimed at “guiding” the search process, in such a way that the search space is efficiently explored.
- Metaheuristic algorithms are usually non-deterministic (that is, they do not use the gradient or Hessian matrix of the objective function.), thus providing near-optimal solutions.
- They include several parameters that must be fitted to the problem at hand, and may incorporate mechanisms to avoid getting trapped in confined areas of the search space.
- More advanced metaheuristic techniques take advantage of the experience gathered from previous searches. This memory is used to guide the current search [12].

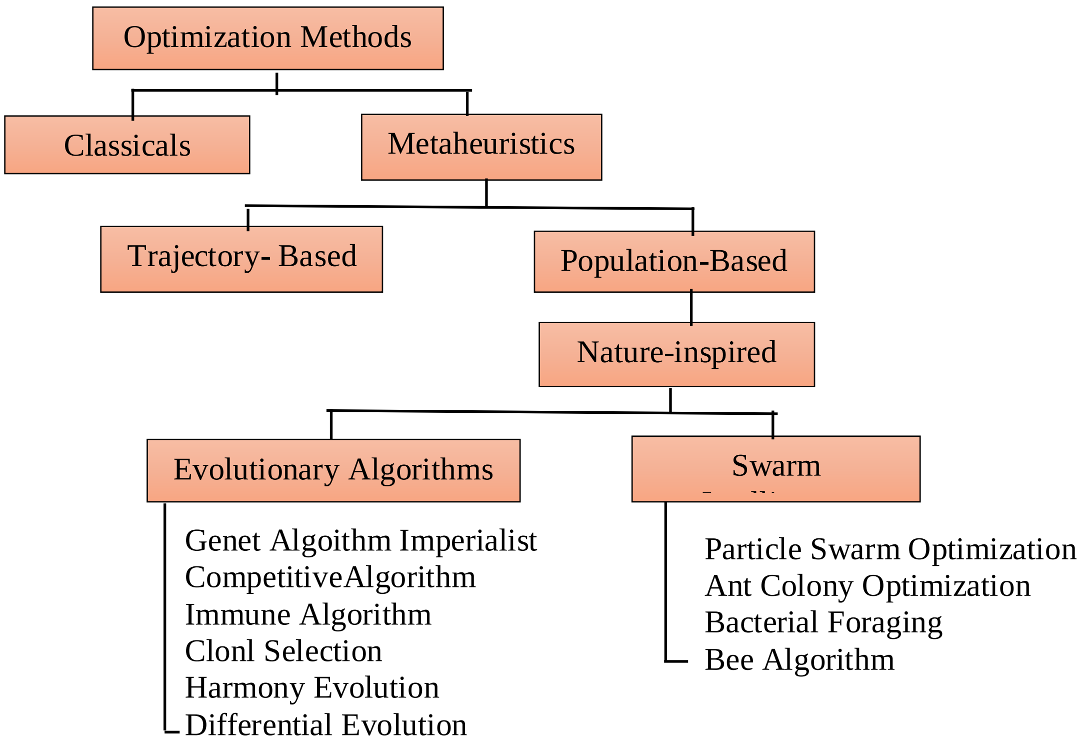

Figure. II.1: Metaheuristics optimization methods classification.

II.2.3 Multi-objective Optimization :

Many optimization problems have multiple (conflicting) objectives, essentially rendering the concept of optimality meaningless since the best solution for one objective may not be the best for another. In multi-objective optimization the concept of dominance is therefore introduced. A solution is said to dominate another solution if its quality is at least as good on every objective and better on at least one. The set of all non-dominated solutions of an optimization problem is called the Pareto set and the projection of this set onto the objective function space is called the Pareto front. The aim of multi-objective metaheuristics is to approximate the Pareto front as closely as possible and therefore generate a set of mutually no dominated solutions called the Pareto set approximation. Notwithstanding some exceptions), most multi-objective metaheuristics belong to the class of evolutionary algorithms. This can be explained by observing that these algorithms naturally operate on a set of solutions. Examples of evolutionary multi-objective metaheuristics are the vector evaluated genetic algorithm (VEGA), the non-dominated sorting algorithm (NDSA) , the multi-objective genetic algorithm (MOGA) and the improved strength pareto evolutionary algorithm (SPEA2) [11].

II.3 Proposed Algorithm:

In this section, the proposed algorithm is explained in details. Firstly, an overview of the basic GSK algorithm is presented in subsection (II.3.1). Then, the new adaptive control settings is introduced in subsection (II.3.2) [15].

II.3.1 GSK algorithm for continuous variables:

An optimization problem is formulated as

$$\min f(x); \qquad X = [x_1, x_2, \dots x_d] \tag{II.1}$$

$$X \in [L_k, L_k]; \quad k = 1,2, \dots , d$$

where f denotes the objective function $X = [x_1, x_2, \dots x_d]$ are the decision variables L_k, L_k are the lower and upper bounds of decision variables, respectively; and d represents the dimension of individuals[19].

Dim is the number of dimensions of an individual. If the problem is to maximize the objective function, then we can consider minimization as (-1* maximization).

The GSK algorithm is a nature-inspired algorithm based on human being behavior and consists of two main phasis: junior phase and senior phase for gaining and sharing the knowledge. All individuals gain the knowledge and then share it back with their own views with other individuals.

The human being at their early stages gains the knowledge from their small surrounding network like members of their families, relatives, neighbors, etc. and they try to share their gained knowledge and opinions with other individuals that may not be from their surrounding networks, due to their inquisitiveness of exploring other members in the population. But they might not be able or have the experience to classify the people in their environment.

Following the same concept, human being with middle or later ages try to enhance their knowledge through interaction with wider network such as colleagues, friends, and social media friends, etc. and try sharing their knowledge and their opinions with the most appropriate person in order to better improve their gained knowledge. Those humans have the required experience to classify people as good or bad, and easily judge them [13].

The mathematical formulation for the above-mentioned process is presented in the following:

Step 1: In the first step, the number of persons are assumed (Number of population size NP). Let x_t (t = 1, 2, . . . , NP) be the individuals of a population. x_{tk} = (x_{t1}, x_{t2}, . . . , x_{td}), where d is branch of knowledge assigned to an individual, and f_t (t = 1, 2, . . . , NP) are the corresponding objective function values. To obtain a starting solution for an optimization problem, an initial population must be obtained. The initial population is created randomly within the boundary constraints as:

$$x_{tk}^0 = L_k + rand_k * (U_k - L_k) \quad \text{(II.2)}$$

Where$rand_k$denotes uniformly distributed random number in the range 0 and 1.[16].

Step 2: At this step, the dimensions of junior and senior stages should be computed through the following formula:

$$Dimj = Dim \times \left(\frac{Gen^{max} - G}{Gen^{max}}\right)^k \quad \text{(II.3)}$$

$$Dims = Dim - Dimj \quad \text{(II.4)}$$

where k(> 0) denotes the learning rate, that monitors the experience rate.$Dimj$ and $Dims$ represent the dimension for the junior and senior stage respectively. Gen^{max} is the maximum count of generations and G is the count of generation.[17]

Step 3: junior gaining-sharing knowledge stage: in this stage, the early aged people gain knowledge from their small networks and share their views with the other people who may or may not belong to their group. Thus individuals are updated as follows:

According to the objective function values, the individuals are arranged in ascending order. For every x_i(i = 1, 2,..,NP select the nearest best x_{i-1} and worst $x_{i+1}$to gain knowledge and also choose randomly (x_r) to share knowledge. *erefore, to update the individuals, the pseudocode is presented in Figure 2[18].

for i=1:NP
$forj = 1: Dim_j$
$if\, rand <= \ K_r \ (Knowledgeratio\ )$
$if\, f(x_i) > f(x_r$
$x_{ij}^{new} = x_i + k_f * [(x_{i-1} - x_{i+1}) + (x_r - x_i)]$
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)

Figure II.2: Pseudo-code for Junior Gaining-Sharing-Knowledge phase.

for i=1:NP
$forj = 1: Dim_s$
$if\, rand <= \ K_r \ (Knowledgeratio\ )$
$if\, f(x_i) > f(x_r$
$x_{ij}^{new} = x_i + k_f * \left[\left(x_{p-best} - x_{p-worst}\right) + (x_{middle} - x_i)\right]$
else
$x_{ij}^{new} = x_i + k_f * \left[\left(x_{p-best} - x_{p-worst}\right) + (x_i - x_{middle})\right]$
end (if)
else $x_{ij}^{new} = x_{ij}^{old}$
end (if)
end (for j)
end (for i)

Figure II.3: Pseudo-code of Senior-Gaining-Sharing knowledge phase.

Where: $\boldsymbol{k_f}$ (>0) represents the knowledge factor.

Step 4: Senior phase: In this stage, the influence of other individuals (good or bad) on the current individual is involved. Updating individuals could be determined as follows:

The candidates in the population are divided into three categories (best individuals, middle individuals, and worse individuals) after sorting all individuals ascendingly based on the values of their objective function.

Number of best individuals = 100p% (***x_{best}***),

Number of middle individuals = NP-2 100p% (***x_{middle}***),

Number of worst individuals 100p%(***x_{worst}***)

Best people100p% (X_{best})	betterpeopleNP-(2 *100p%) (X_{middle})	Worstpeople100p% (X_{worst})

where p represents the partition size ratio relative to the population size. i.e., if p = 0.1, so the best people category is 10% of the population size, the worst people category is 10% of the population size, and better people partition is 80% of the population size.

For each individual x, the top (best) and bottom (worst) 100% individuals were chosen for gaining and the third indi- vidual (better individual) is selected for the sharing. There- fore, updating of the new individual is done through the following pseudo-code presented in (Figure2).

(Figure 3) represents the pseudocode of GSK algorithm. Whereas (Figure 5) represents the flow chart for the GSK algorithm.

begin
G=0,initialize parameters: N, k_f, k_r, kandp
create a random initial population x_i, $i = 1,2, \ldots \ldots \ldots N$
evaluate $f(x_i)$,$\forall i, = 1,2, \ldots \ldots \ldots N$
for G=1 to GEN^{max}
compute the number of
(gained and shared dims. of both phases)
using experience eqs.(2),(3);
//Junior gainig-sharing knowledge phase //
//Senior gainig-sharing knowledge phase //
if if $f(x_i^{new}) \leq f(x_i^{oid})$,
$x_i^{old} = x_i^{new}$, $f(x_i^{old}) = f(x_i^{new})$
end // update each vector
if if $f(x_i^{new}) \leq f(x_{best}^G)$,
$x_{best}^G = x_i^{new}$, $f(x_{bes}^G) = f(x_i^{new})$
end // update global best
end for ……….N
end for ………G
end for   begin

Figure II.4: Pseudo code of GSK algorithm.

```
Begin
 Initialize parameter setting pool , initialize Kw P
    ( while nf es < max _nf es)
              If (nf es >0.1*max _nf es)
                 Update Kw P
                End if
Assign one setting to each individual according to
Kw P x_i^new =generatenew individuals usig
                 GSKEvaluate the improvement of es
                 Calculate the improvement of each setting
     End While
End Begin
```

Figure II.5: Pseudo code for the adaptation process.

II.3.2 Adaptation schemes of parameters in APGSK

The effective performance of GSK algorithm is remarkably depending on choosing the values of its control parameters: knowledge factor K_f, knowledge ratio K_r, knowledge rate K and population size N. Figure 4 represents the pseudo code of the adaptation process.

II.3.2.1 Control adaptive settings for (K_f and K_r)

The process of adapting the control parameters begins by choosing a pool for the two parameters and probability parameter Kw_P. The pool used for setting the parameters consists of the following two pairs (K_f, K_r): [(0.1, 0.2), (1.0, 0.1), (0.5, 0.9), and (1.0, 0.9)] which is applied during first 50% of MAX_{NFT}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 MAX_{NFT} with probability less than 0.3 for enhancing the diversity of the population to ensure escaping from local optima and to reduce possibility of stagnation. The probability parameter Kw_Pincludes a probability parameter p for each setting of the above-mentioned pool of settings. Therefore, every individual in the population will be assigned only one setting according to its probability parameter p.

The probability parameter adaptation Kw_P will start after 10% of the function evaluations. The adaptation of the prob- ability parameter will depend on the performance of each

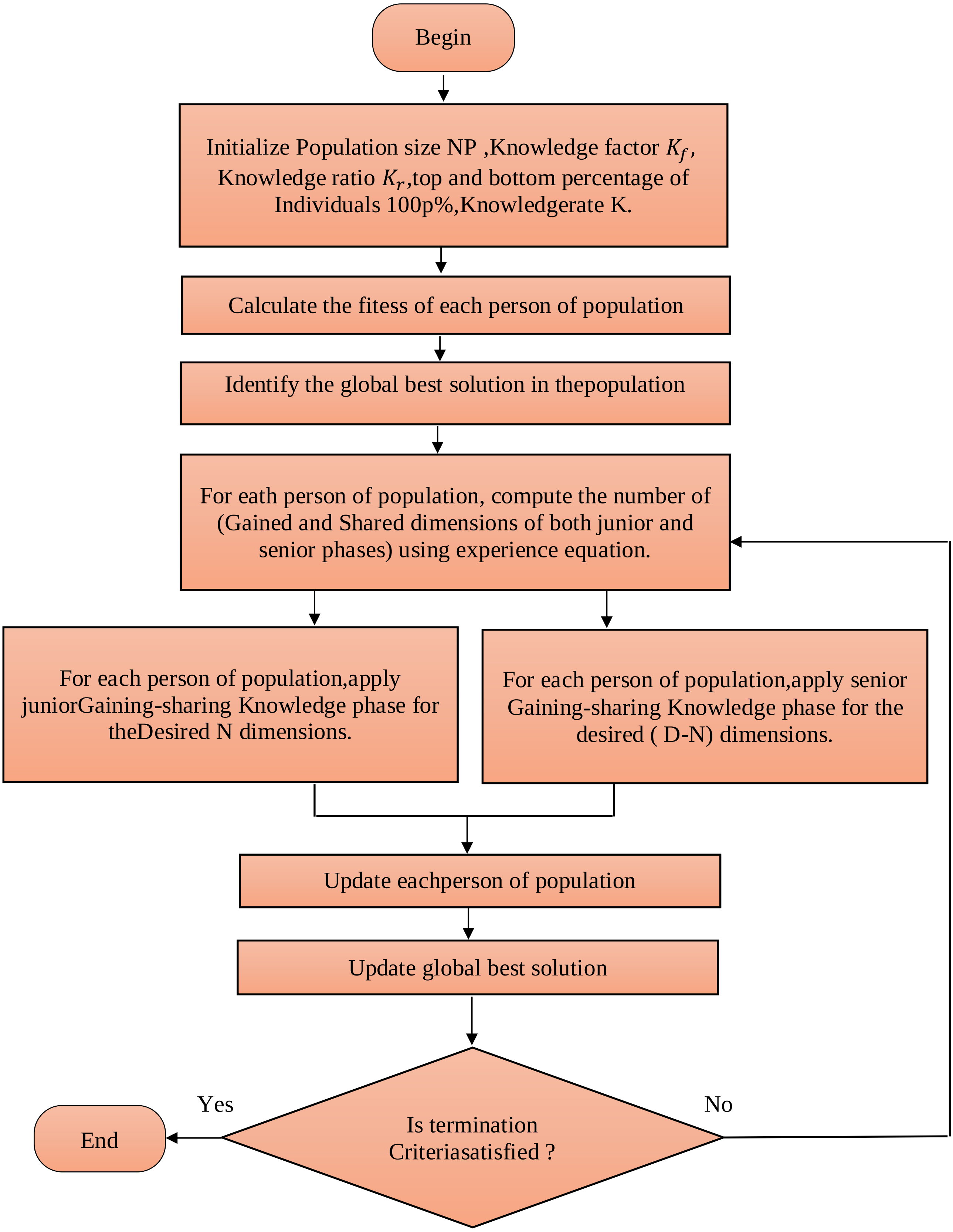

Figure II.6: Flow chart of GSK algorithm.

setting via the following formula:

$$\omega_{ps} = \sum_{i=1}^{n} f(x_i^{new}) - f\left(x_i^{old}\right) \tag{II.5}$$

where ω_{ps}cop 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^{old} is the new solution,x_i^{new} is the old solution, and n represents the number of solutions that belong to the parameter setting ps. After that, the improvement rate (A_{ps}) could be calculated for each parameter setting by:

$$\Delta_{ps} = \max(0.05, \omega_{ps}/sum(\omega_{ps})) \tag{II.6}$$

0.05 is used to express the minimum probability that could be assigned for each parameter setting in order to guarantee that all settings have a probability of being selected. The improvement rate(A_{ps}) for each parameter setting is used for updating $Kw_{\,P}$ due to the following formula:

$$Kw_{P_{g+1}} = (1-c)Kw_{P_g} + \mathrm{c}.\Delta_{ps} \tag{II.7}$$

where c represents the learning rate. A constant learning rate c is used in order to make a benefit from the cumulative knowledge about each parameter setting's performance.

II.4 Population size reduction:

To improve the performance of APGSK, Non-Linear Population Size Reduction (NLPSR) scheme is used. Non-linear function in APGSK was:

$$N_{G+1} = round\left[\left(N^{min} - N^{init}\right) * \left(\left(\frac{NFE}{MAX_{NFT}}\right)\right)^{\left(1-\left(\frac{NFE}{MAX_{NFT}}\right)\right)} + N^{init}\right] \tag{II.8}$$

Where NFE is presenting the current number of functions evals, MAX_{NFT} is the max allowable number of functions evals, the size of the population initially generated is represented by N^{init}, and N^{min} = 12 is the min number of candidates that is appropriate for APGSK in order to keep the best and worst partitions have more than one individual in each partition.

II.5 The settings of knowledge rate k:

Indeed, for simulating the gaining & sharing knowledge process during the human being life span for a specific population, the diverse nature of any population should be considered. Therefore, the knowledge rate k must take into consideration both scenarios, the first scenario when k∈ (0, 1), and the second scenario when k > 1 with probability of (NFE/MAX_{NFT}). So for each individual in the population, if rand > (NFE/MAX_{NFT}), k = 0.5 else k = 2. [13]

II.6 Conclusion :

In this chapter, we reviewed optimization problems in life , and since optimization algorithms have great power to solve nonlinear , complex and difficult optimization problems , nature-inspired algorithms have been widely applied, and after the development of many metaheuristic algorithms, that's what motivated us to try the optimization algorithm (GSK).

However, it is important to recognize that the algorithms are not flawless either intentionally or unintentionally. This can lead to the conclusion of false information or the exclusion of certain points of view, prompting us to make a great effort to avoid making mistakes.

Chapter III:

Simulations and Results

III.1. Simulation Results and Discussions:

In order to solve the dynamic combined economic environmental dispatch problem, we developed and executed the GSK algorithms in MATLAB R2022b, and they were run on a personal computer with an Intel Core (TM) i5 with a processor of 2.11 GHz and a Ram of 8.0 GB under MS Windows 11. In the first part, the GSK proposed techniques were tested on the unit test system by considering VPE for case studies, and in the second part, the GSK method was applied on the IEEE three-unit system, including VPE, for three cases. The constraints involved in all cases were power balance limit with consideration of transmission losses and generator operating limits constraints. The obtained results were compared with the optimization approaches recently published in the literature. Table 1 stands for the parameter values of GSK algorithms, for all cases studies.

Table III.1: Parameters of GSK algorithms for DEED problem.

Algorithm	Parameters
GSK	population size(NP) changes from 50 to 140 & 5 runs number & MAXNFES 200000 to optimize the solutions for System cases.

III.1.1 Test system 1: (Six-Generator) Best Solution For A Smooth Cost Function .

Power demand: 1263 (MW)

Consider a power plant consisting of (Six- Generators) is considered. The parameters of the Generators are shown in **TableIII.2**.

Table III.2: The data of Generators

Generators	Power limit (MW)		Cost Coefficients		
	P(min)	P(max)	a	b	c
1	100	500	0.0070	7.0	240
2	50	200	0.0095	10.0	200
3	80	300	0.0090	8.50	220
4	50	150	0.0090	11.0	200
5	50	200	0.0080	10.50	220
6	50	120	0.0075	12.0	190

The B matrix of the test system we use is given by Equation

$$B = \begin{bmatrix} 1.7 & 1.2 & 0.7 & -0.1 & -0.5 & -0.2 \\ 1.2 & 1.4 & 0.9 & 0.1 & -0.6 & -0.1 \\ 0.7 & 0.9 & 3.1 & 0.0 & -1.0 & -0.6 \\ -0.1 & 0.1 & 0.0 & 0.24 & -0.6 & -0.8 \\ -0.5 & -0.6 & -0.1 & -0.6 & 12.9 & -0.2 \\ 0.2 & -0.1 & -0.6 & -0.8 & -0.2 & 15.0 \end{bmatrix}$$

Table III .3: Six-generator test system, smooth cost: comparison on robustness Comparison of the Best Solution.

Method	Max ($/h)	Min ($/h)	average ($/h)	Std
GA binary [20]	15519.87	15451.66	15469.21	NA
GA[20]	15524.00	15459.00	15469.00	NA
NPSO-LRS5 [20]	15609.64	15450.0	15454.00	NA
SOHPSO [20]	15609.64	15446.02	15497.35	NA
GAAPI [20]	15449.85	15449.78	154497.81	NA
GSK	15444.20	15444.19	15444.19	**32483.28**

TableIII.4: Six-Generator Test System Best Solution for A Smooth Cost Function[20].

Unit output (MW)	LM	GA binary	RCGA	NPSO-LRS	SOH-PSO	GAAPI	GSK
P1	447.00	456.46	474.81	446.96	447.49	447.12	446.71
P2	173.50	168.26	178.64	173.39	173.32	173.41	173.5
P3	264.00	258.68	262 .21	262.34	263.47	264.11	262.79
p4	138.50	132.66	134.28	139.51	139.06	138.31	143.48
P5	166.04	170.97	151.90	164.70	165.47	166.02	163.91
p6	87.00	89.10	74.18	89.01	87.13	87.00	85.35
Losses	13.00	13.13	13.02	12.93	12.55*	12.98	12.39
Total output	1276.00	1276.13	1276.03	1275.94	1275.55	1275.97	1275.39
Génération cost ($/h)	15450.00	15451.66	15459.00	15450.0	15446.02	15449.7	15444.18

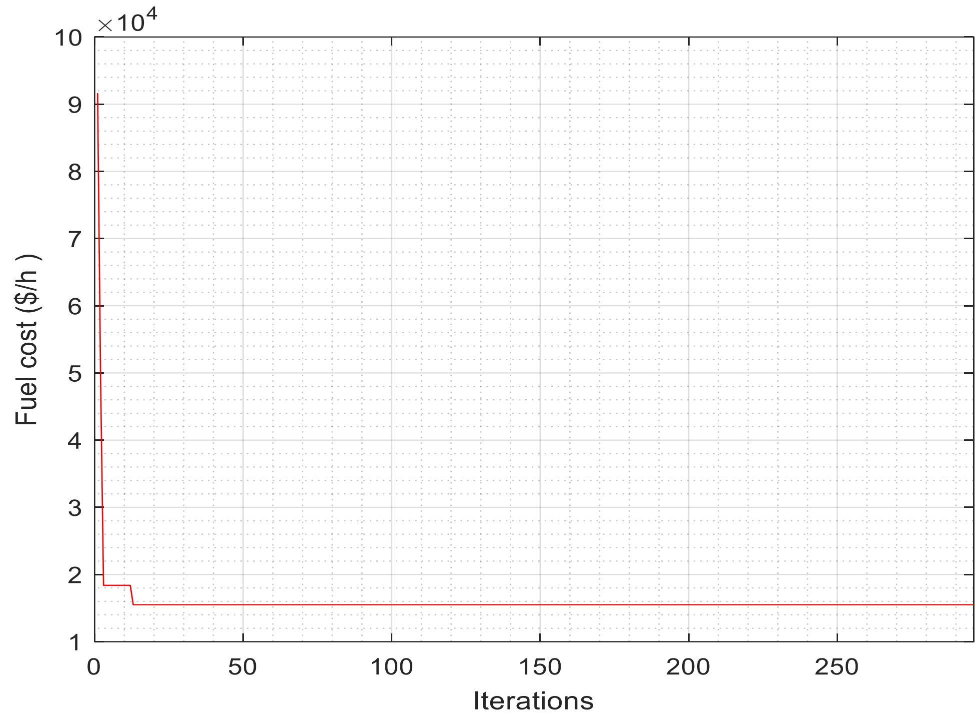

Figure.III.1: Convergence characteristics of GSK algorithms for fuel cos

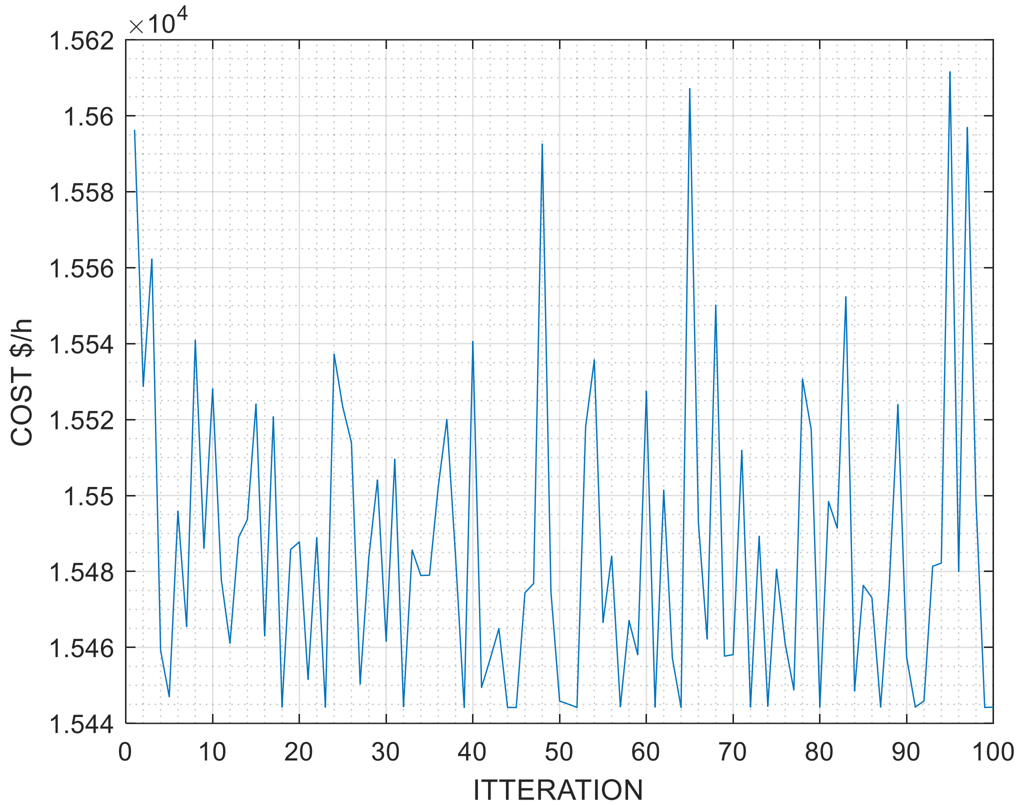

Figure.III.2: variation the best of cost function the number of runs: 6-generator test system with no smooth cost of generation.

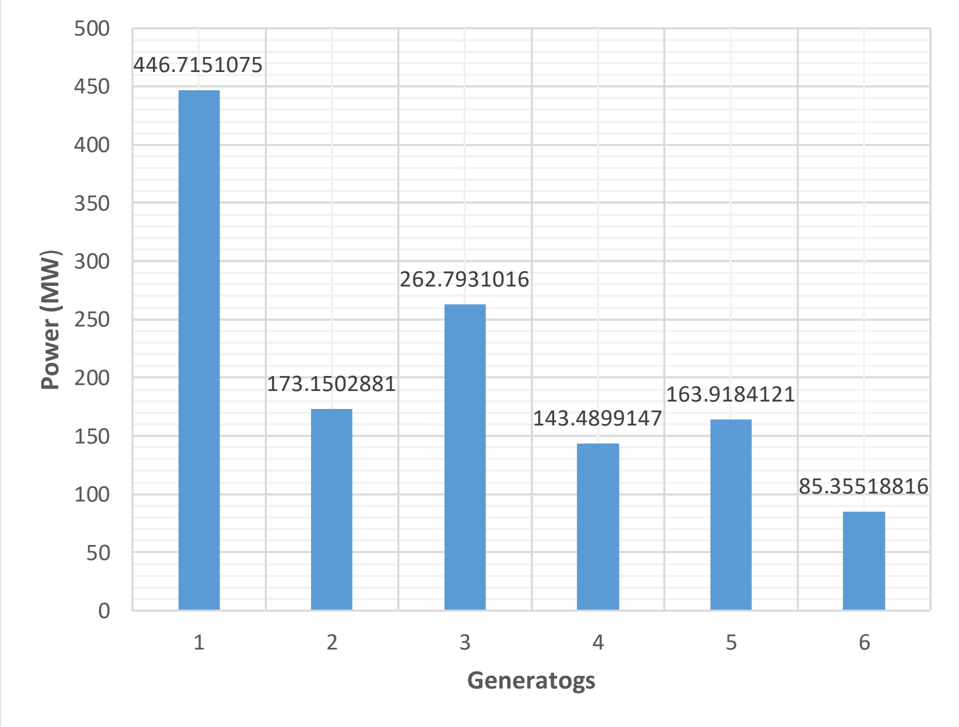

Figure III.3: Generated power

Comparative results of optimization techniques (LM, GA binary, RSGA, NPSO-LRS, SUH-PSO, GABI, and GSK) The statistical analysis of the optimal results is presented in Table 2. Of the best values, the power and effectiveness of the proposed GSK in finding the optimal The solutions to the EPD problem are compared with a reasonable number of iterations and The restrictions have been checked. The results shown in Table 2 show the cost found by the GSK algorithm, which It is equal to 15444.18($/h), less expensive compared to the cost values of the algorithms shown in **Table III. 4**.

III.1.2 Test system 2:(Three-Generator) Best Solution for A Smooth Cost Function.

III.1.2.1 Case 1:

Table III.5: The data of Generators [7].

DG sources	Min Power (MW)	Max Power (MW)	u ($/$MW^2$h)	v ($/MWh)	w ($/h)	x (kg/MW^2h)	y (kg/MWh)	z (kg/h)
G1	37	150	0.0024	21	15.30	0.0105	-1.355	60
G2	40	160	0.0029	20.16	992	0.008	-0.6	45
G3	50	190	0.021	20.4	600	0.012	-0.555	90

Table III.6: Statistical Results for The 3-Generator Test System

Method	Min ($/h)	Max ($/h)	Median ($/h)	Mean ($/h)	Std ($/h)
GSK	11332.29	473115.9	11332.29	95529.76	211077.1

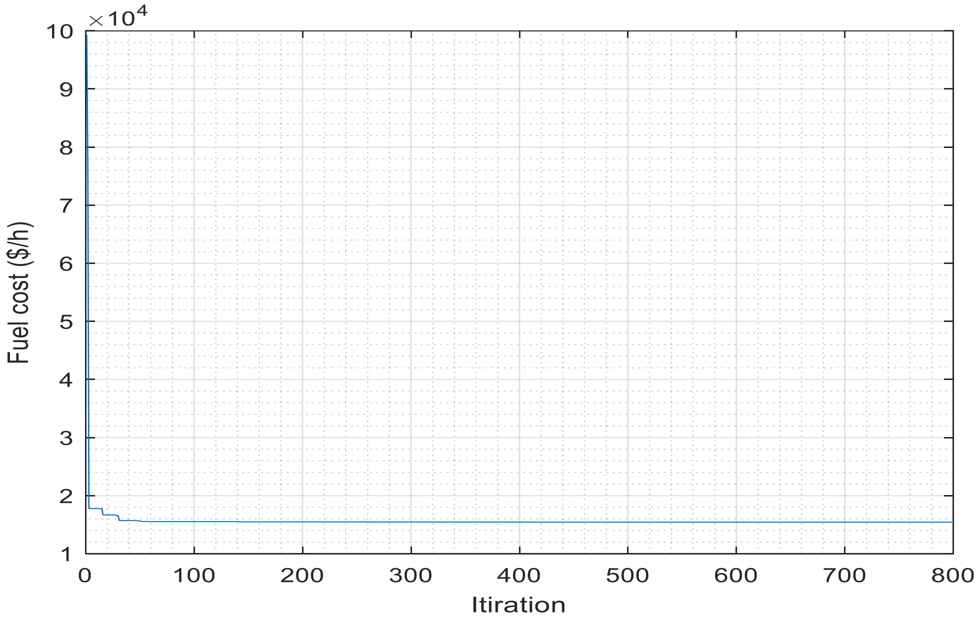

Figure.III.4: Convergence characteristics of GSK algorithms for fuel cos

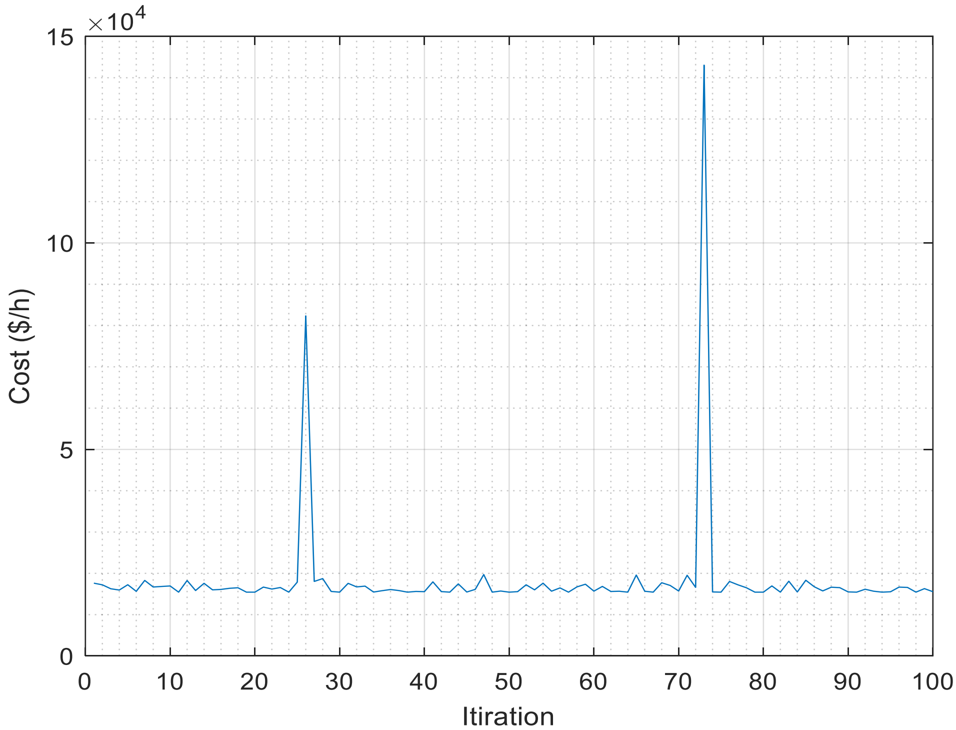

Figure.III.5: consistency of results over 5 independent runs: 3-generator test system with no smooth cost of generation.

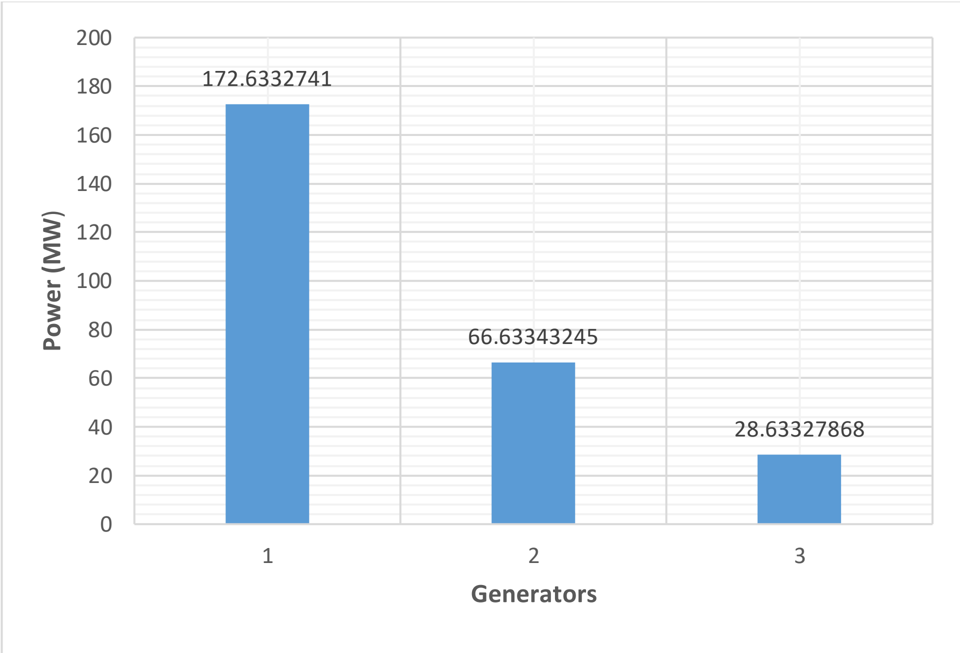

Figure.III.6: Generated power

III.1.2.2 Case 2:(Three-Generator without RES) Best Solution for A Smooth Cost Function and emission.

Table III.7: Generator power limits, fuel cost coefficients and emission coefficients [7].

DG sources	Min Power(MW)	Max Power (MW)	u ($/$MW^2$h)	v ($/MWh)	w ($/h)	x (kg/MW^2h)	y (kg/MWh)	z (kg/h)
G1	37	150	0.0024	21	15.30	0.0105	-1.355	60
G2	40	160	0.0029	20.16	992	0.008	-0.6	45
G3	50	190	0.021	20.4	600	0.012	-0.555	90

TableIII.8: Simulation results of best solutions the cost of GSK.

Times	Load	PG1	PG2	PG3	Cost
1,00	140	37,0000137	52,9999964	50,0000212	6051,4117
2,00	150	37,0000308	63,0000071	50,0000112	6260
3,00	155	37,0000341	68,0000176	50,0000008	6360
4,00	160	37,0000423	72,9999526	50,0000494	6460
5,00	165	37,0000458	78,0000049	50,0000256	6560
6,00	170	37,0000114	83,0000446	50,000048	6670
7,00	175	37,0000019	87,999956	50,0000207	6770
8,00	180	37,0000112	92,9999901	50,0000309	6870
9,00	210	37,0000035	123,000021	50,0000445	7500
10,00	230	37,0000416	143,000039	50,0000088	7920
11,00	240	37,0000101	152,999992	50,0000347	8130
12,00	250	39,9999768	159,999966	50,0000206	8340
13,00	240	37,0000242	152,999975	50,0000441	8130
14,00	220	37,0000353	133,000044	50,0000186	7710
15,00	200	37,0000351	112,999988	50,0000009	7290
16,00	180	37,0000391	93,0000249	50,0000144	6870
17,00	170	37,000018	83,0000189	50,0000433	6670
18,00	185	37,0000377	98,000024	50,0000193	6980
19,00	200	37,0000128	113,000011	50,0000197	7290
20,00	240	37,0000146	153,000023	50,0000285	8130
21,00	225	37,0000406	137,999967	50,0000093	7810
22,00	190	37,0000391	102,999978	50,0000191	7080
23,00	160	37,0000037	73,0000249	50,0000381	6460
24,00	145	37,0000124	58,0000386	50,0000169	6150
					170460,878

TableIII.9: Cost Comparaison

Algorithm	cost ($/h)
PSO	176177.9174
DE	176169.0719
SOS	176168.04244
GWO	176167.8827
WOA	176166.5662
GSK	**170460,8780**

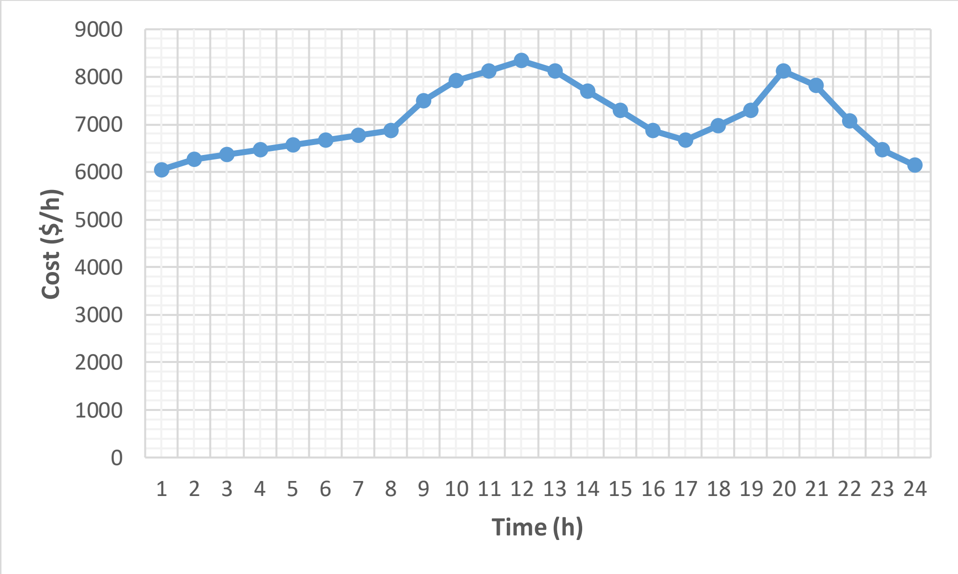

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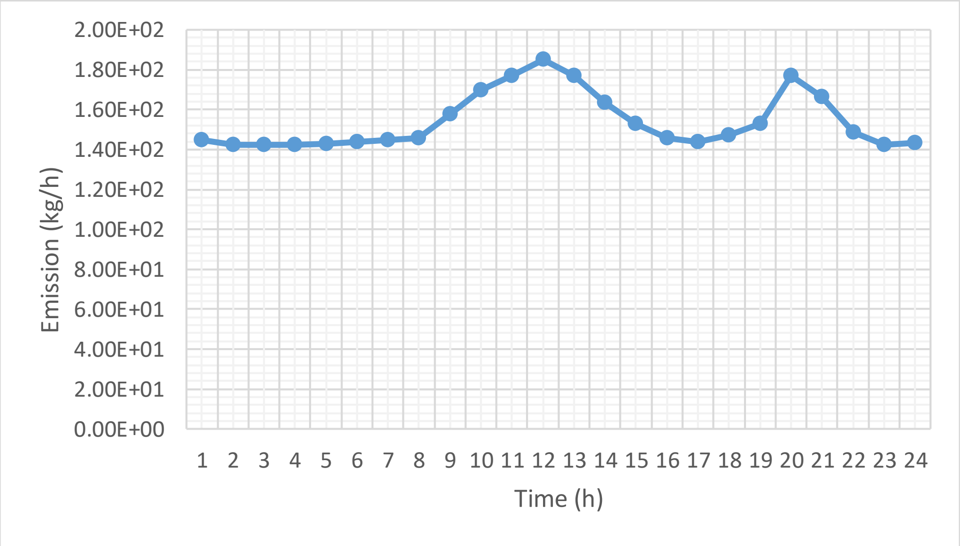
Figure III.7: Hourly sharing of costs (in $/hr.) for all the cases for DED using GSK.

TableIII.10: Simulation results of best emission solutions of GSK.

Times	Load	PG1	PG2	PG3	Emiss
1,00	140	50,0000236	40,0000454	50,0000051	145
2,00	150	59,9999759	40,0000022	50,0000206	143
3,00	155	65,0000175	40,0000134	50,0000202	142
4,00	160	67,9729838	42,0269602	50,0000021	143
5,00	165	70,1350586	44,8649213	50,000011	143
6,00	170	72,297343	47,7026753	50,0000062	144
7,00	175	74,4595172	50,5405066	50,0000315	145
8,00	180	76,6215783	53,3783597	50,0000378	146
9,00	210	89,5946046	70,405422	50,0000095	158
10,00	230	97,4182963	80,6740313	51,9076919	170
11,00	240	100,555496	84,7917295	54,6527744	177,069965
12,00	250	103,692821	88,9092687	57,3979255	184,966044
13,00	240	100,555464	84,791737	54,6527913	177,069965
14,00	220	93,9189112	76,0811078	50,000008	163,265878
15,00	200	85,2702993	64,729686	50,000002	152,736149
16,00	180	76,6216094	53,3783618	50,0000046	145,838851
17,00	170	72,2972783	47,7027055	50,0000309	143,752365
18,00	185	78,7838433	56,2161715	50,0000224	147,222635
19,00	200	85,2703431	64,7297029	50,0000269	152,736149
20,00	240	100,555494	84,7917419	54,6528018	177,069965
21,00	225	95,8496536	78,6152089	50,5351051	166,461142
22,00	190	80,9459346	59,0540978	50,0000212	148,833446
23,00	160	67,9730262	42,0270101	50,0000123	142,573986
24,00	145	55,0000475	40,000022	50,0000397	143,2875
		1920,78962	1435,41149	1223,7994	3700

TableIII.11: Emission Comparaison.

Algorithm	Emission ($/Kg)
PSO	2385.7962
DE	2383.2908
SOS	2381.9505
GWO	2380.519
WOA	2379.4554
GSK	3700



. **Figure III.8:** Hourly sharing of emission (in $/hr.) for all the cases for DED using GSK.

III.1.2.3 Case 3: (Three-Generator with RES) Best Solution For A Smooth Cost Function and emission.

Table III.12: Generator power limits, fuel cost coefficients and emission coefficients [7].

DG sources	Min Power(MW)	Max Power (MW)	u ($/$MW^2$h)	v ($/MWh)	w ($/h)	x (kg/MW^2h)	y (kg/MWh)	z (kg/h)
G1	37	150	0.0024	21	15.30	0.0105	-1.355	60
G2	40	160	0.0029	20.16	992	0.008	-0.6	45
G3	50	190	0.021	20.4	600	0.012	-0.555	90

TableIII.13: Day ahead forecasted hourly output of PV and WT and hourly load demand [7].

Times	Load	PV	WT
1,00	140	0	1,7
2,00	150	0	8,5
3,00	155	0	9,27
4,00	160	0	16,66
5,00	165	0	7,22
6,00	170	0,03	4,91
7,00	175	6,27	14,66
8,00	180	16,18	25,56
9,00	210	24,05	20,58
10,00	230	39,37	17,85
11,00	240	7,41	12,8
12,00	250	3,65	18,65
13,00	240	31,94	14,35
14,00	220	26,81	10,35
15,00	200	10,08	8,26
16,00	180	5,3	13,71
17,00	170	9,57	3,44
18,00	185	2,31	1,87
19,00	200	0	0,75
20,00	240	0	0,17
21,00	225	0	0,15
22,00	190	0	0,31
23,00	160	0	1,07
24,00	145	0	0,58

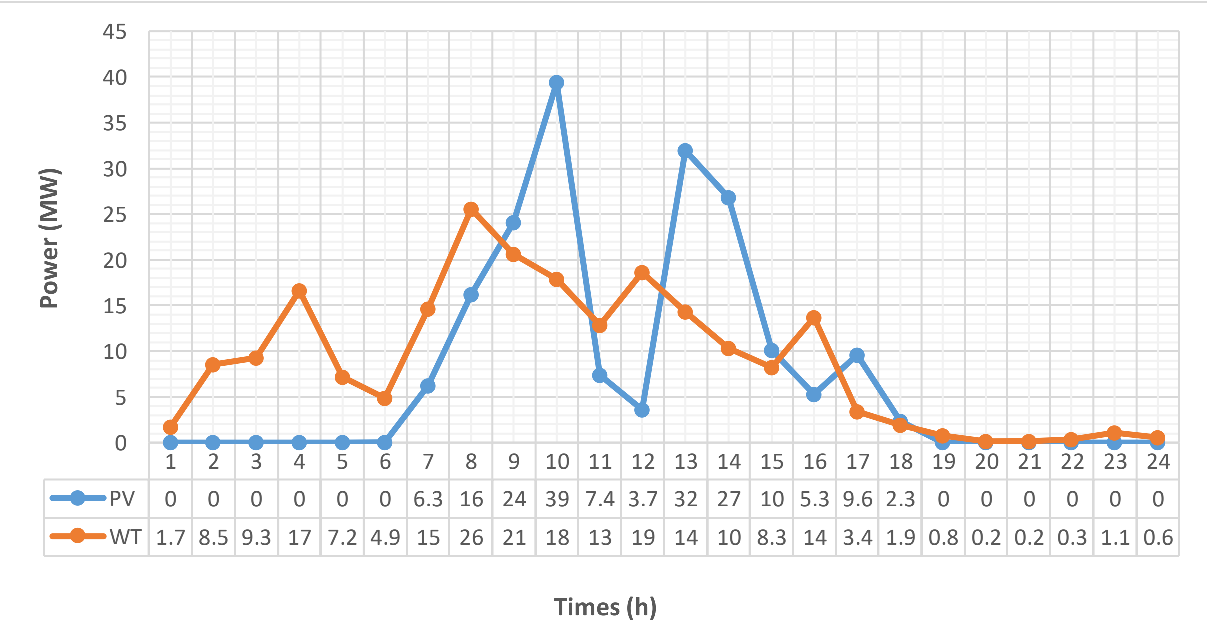


Figure III.9: Curve PV and WT Every hour within a day

TableIII.14: Simulation results of best solutions with PV and WT the cost of GSK.

Times	Load	PV	WT	PG1	PG2	PG3	TOTAL COST
1	140	0	1,7	37,0000307	51,3000395	50,0000037	138,300074
2	150	0	8,5	37,0000385	54,4999514	50,0000352	141,500025
3	155	0	9,27	37,0000285	58,7299584	50,0000347	145,730022
4	160	0	16,66	37,0000493	56,339986	50,0000046	143,34004
5	165	0	7,22	37,0000362	70,7800038	50,0000093	157,780049
6	170	0,03	4,91	37,0000367	78,0600112	50,0000294	165,060077
7	175	6,27	14,66	37,000023	67,0700041	50,0000397	154,070067
8	180	16,18	25,56	37,0000123	51,2599673	50,0000256	138,260005
9	210	24,05	20,58	37,0000455	78,3699561	50,0000123	165,370014
10	230	39,37	17,85	37,0000264	85,7800076	50,0000143	172,780048
11	240	7,41	12,8	37,0000442	132,789969	50,000028	219,790041
12	250	3,65	18,65	37,0000257	140,700041	50,0000386	227,700105
13	240	31,94	14,35	37,0000135	106,710002	50,0000034	193,710018
14	220	26,81	10,35	37,000048	95,8399746	50,0000402	182,840063
15	200	10,08	8,26	37,0000128	94,6599694	50,0000254	181,660008
16	180	5,3	13,71	37,0000383	73,9900036	50,0000065	160,990048
17	170	9,57	3,44	37,0000463	69,9899659	50,0000298	156,990042
18	185	2,31	1,87	37,0000168	93,8200376	50,0000278	180,820082
19	200	0	0,75	37,0000122	112,250047	50,000041	199,2501
20	240	0	0,17	37,0000353	152,83	50,0000005	239,830036
21	225	0	0,15	37,0000425	137,850025	50,0000463	224,850114
22	190	0	0,31	37,0000087	102,689982	50,0000195	189,69001
23	160	0	1,07	37,000021	71,9300275	50,0000094	158,930058
24	145	0	0,58	37,0000409	57,4200229	50,0000009	144,420065

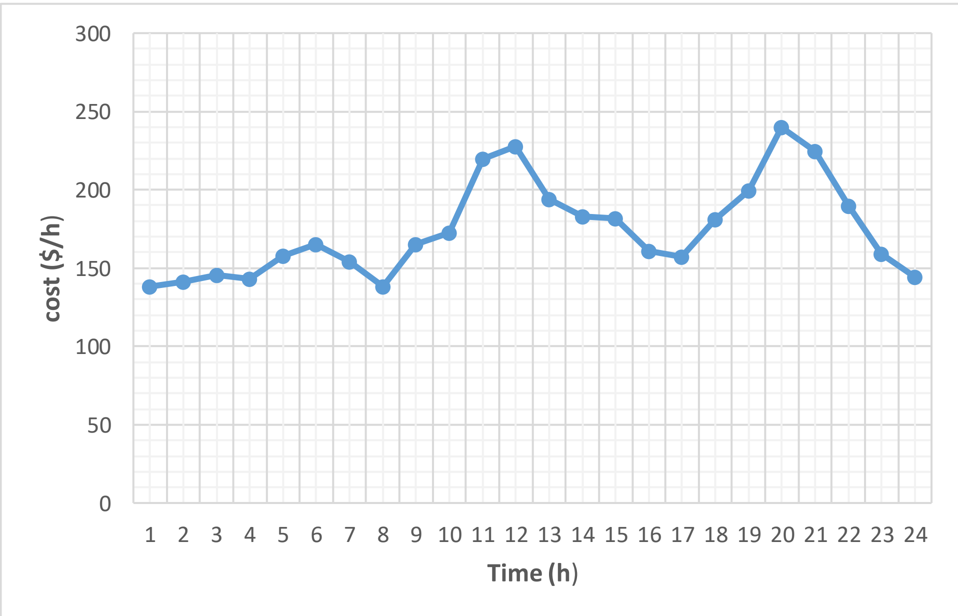


Figure III.10: Hourly sharing of costs (in $/hr.) for all the cases for DED using GSK

TableIII.15: Simulation results of best solutions with PV and WT the emission of GSK.

Times	Load	PV	WT	PG1	PG2	PG3	Emiss
1	140	0	1,7	48,299955	40,0000157	50,0000042	983
2	150	0	8,5	51,5000034	40,0000079	50,0000226	259
3	155	0	9,27	55,7300181	40,0000069	50,0000231	269
4	160	0	16,66	53,3400048	40,0000144	50,0000193	383
5	165	0	7,22	67,013017	40,767044	50,0000042	236
6	170	0,03	4,91	70,1610704	44,8989092	50,000042	203
7	175	6,27	14,66	64,0699984	40,0000095	50,0000313	693
8	180	16,18	25,56	48,2600413	40,0000461	50,0000284	141
9	210	24,05	20,58	70,2950701	45,0748946	50,0000363	176
10	230	39,37	17,85	73,4994832	49,280525	50,0000259	256
11	240	7,41	12,8	93,8280732	75,961906	50,0000053	7507,0212
12	250	3,65	18,65	96,6966589	79,7269989	51,2763026	6393,46148
13	240	31,94	14,35	82,5502856	61,1596673	50,0000187	21048,1498
14	220	26,81	10,35	77,8497005	54,9903482	50,0000025	17581,8333
15	200	10,08	8,26	77,3394546	54,3204681	50,0000307	8093,23092
16	180	5,3	13,71	68,4010748	42,5888904	50,0000007	6257,40031
17	170	9,57	3,44	66,6714134	40,3186278	50,000022	7017,13987
18	185	2,31	1,87	76,9762457	53,8437526	50,0000306	2854,18018
19	200	0	0,75	93,8200376	50,0000278	50,0000096	1491,76138
20	240	0	0,17	100,502169	84,7217356	54,6060733	1641,96211
21	225	0	0,15	95,8025761	78,5533968	50,4940001	1538,63649
22	190	0	0,31	80,8118849	58,87814	50,000023	1382,8955
23	160	0	1,07	67,5103489	41,4196625	50,0000007	1413,29692
24	145	0	0,58	54,4200233	40,0000448	50,000016	1362,35169

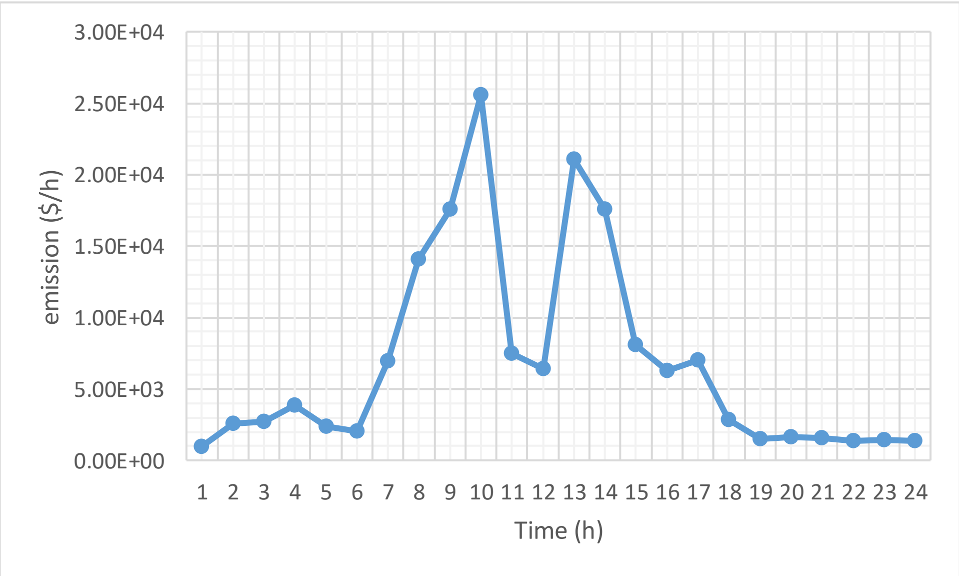


Figure III.11: Hourly sharing of emission (in $/hr.) for all the cases for DEED using GSK

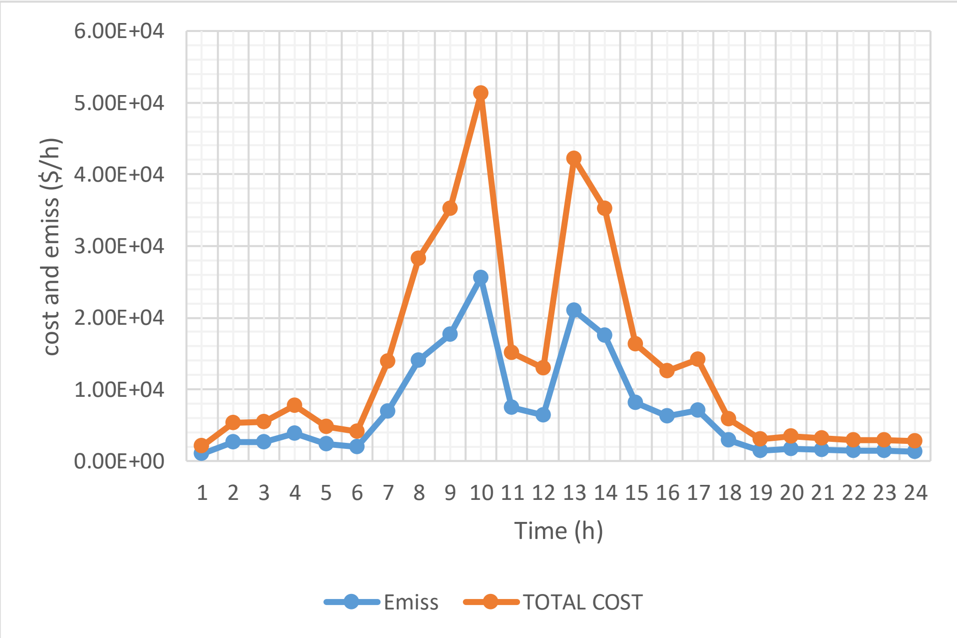


Figure III.12: Hourly sharing of cost and emission (in $/h.) for all the cases for DED using GSK

III.2: Conclusions and Future Work

In this the work, New optimization methods were proposed, presented and applied to solve the problem of dynamic economic emission transfer of generator units technologies are the fact that metaheuristic algorithms are easy to implement and can be used for a variety of other problems. The proposed strategies are validated by Matlab simulations and testing on both standard IEEE Power Systems, and 6-module and 3-module systems. The numerical results of this system are presented to demonstrate the capabilities of the proposal algorithms for creating the optimal solution to the problem of the dynamics of sending economic emissions combined in several segments. From Tables 10, 11 and 15, it is clear that the optimal system generation table of 6 modules and 3 modules obtained by GSK meet the limit of the power balance while considering the power loss and generator operating limit limits. The proposed GSK gives better performance compared to the methods mentioned in the literature. In all cases, the proposed algorithms can reach the optimal solution more quickly. In future works, we intend to combine the Canadian Space Agency and the Transportation Security Administration, introducing them to other types of optimization issues, such as large-scale economic load transfer problems, integrated renewable energy sources, multi-target ed problems with many complex limitations.

General conclusion:

In conclusion, economic power dispatch (EPD) is a complex optimization problem with significant implications for the economic efficiency, reliability, and sustainability of electrical power systems. The development and application of advanced optimization techniques and algorithms are crucial for finding optimal generation schedules that minimize costs, ensure grid stability, and support environmental goals. As technology continues to advance, the field of economic power dispatch will continue to evolve, providing more sophisticated and effective solutions to meet the growing demands of the power sector.

the application of gaining-sharing knowledge based algorithms can be highly beneficial in solving economic power dispatch problems. Economic power dispatch is a crucial task in the field of electrical power systems, aiming to optimize the allocation of power generation among different units , minimizing costs and emission. while considering various constraints

In this thesis, we propose a new metaheuristic algorithm called GSK to solve this the problem.

Having obtained the results, we made a comparison of the solutions of our approach obtained from this algorithm with the results of the values of the previously studied algorithms. We found that the results obtained were satisfactory in terms of significantly reducing the cost of fuel, reducing emissions and combined thermal energy.

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