HYBRID OPTIMIZATION SEARCH ALGORITHM TO SOLVE CEED OF POWER SYSTEM INCLUDING SOLAR PHOTOVOLTAIC GENERATION

Abdurazaq Mohamed Ali ELBAZ

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Assoc. Prof. Dr. Muhammet Tahir GÜNEŞER

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Abdurazaq Mohamed Ali ELBAZ

T.C.
Karabuk University
Institute of Graduate Programs
Department of Electrical and Electronics Engineering
Prepared as
Ph.D. Thesis

Thesis Advisor
Assoc. Prof. Dr. Muhammet Tahir GÜNEŞER

KARABUK
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I certify that in my opinion the thesis submitted by Abdurazaq Mohamed Ali ELBAZ titled “HYBRID OPTIMIZATION SEARCH ALGORITHM TO SOLVE CEED OF POWER SYSTEM INCLUDING SOLAR PHOTOVOLTAIC GENERATION” is fully adequate in scope and in quality as a thesis for the degree of Doctor of Philosophy.

Assoc. Prof. Dr. Muhammet Tahir GÜNEŞER ....
Thesis Advisor, Department of Electrical & Electronics Engineering

This thesis is accepted by the examining committee with a unanimous vote in the Department of Electrical & Electronics Engineering as a Ph.D thesis. January 25, 2022

<u>Examining Committee Members (Institutions)</u>		<u>Signature</u>
Chairman	: Prof. Dr. Mehmet KARALI (NEU)	....
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Director of the Institute of Graduate Programs

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Abdurazaq Mohamed Ali ELBAZ

ABSTRACT

Ph.D. Thesis

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Thesis Advisors:
Assoc. Prof. Dr. Muhammet Tahir GÜNEŞER
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The main objective of our research is to enable electric power systems to work economically and minimize all losses as much as possible. Optimization methods are the most effective way of solving the economic dispatch problem and so reduce the cost of system operations, especially for reducing the generating units' fuel expenditures and cutting transmission losses. This economic operation must be achieved by sharing total load demand among all generating units, according to the minimum cost for each unit, taking into consideration the efficiency and reliability of this process. The main target of using this process is to obviate wasting extra money on system operations; in return, this money can be saved. Many optimization methods were employed to solve the economic dispatch problem, and among the most recent and efficient algorithms is the hybrid bat-crow search algorithm, which is original to this study. In this thesis, we will employ optimization methods for a part of generating units with the aim of solving the economic power dispatch for the system. We will employ the most well-known algorithms, such as the bat algorithm, particle swarm optimization (PSO), and genetic algorithm (GA). Our aim is to solve the economic dispatch and combined economic emission dispatch (CEED) problems in power systems. We will compare the proposed hybrid bat-crow search algorithm results with bat, crow search, GA, and PSO algorithm for various power systems. For the solar energy we will use Center of Solar Energy and Research Studies Tripoli/Libya data.

Keywords : Combined Emission and Economic Dispatch, Power System, Solar Photo Voltaic Generation, Optimization Method.

Science Code : 90544

ÖZET

Doktora Tezi

GÜNEŞ FOTOVOLTAİK ÜRETİMİ DAHİL HİBRİT OPTİMİZASYON ARAMA ALGORİTMASI

Abdurazaq Mohamed Ali ELBAZ

Karabük Üniversitesi
Lisansüstü Eğitim Enstitüsü
Elektrik-Elektronik Mühendisliği

Tez Danışmanı:
Assoc. Prof. Dr. Muhammet Tahir GÜNEŞER
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Çalışmamızın temel amacı, elektrik güç sisteminin ekonomik olarak çalışmasını sağlamak ve tüm kayıpları mümkün olduğunca asgari düzeye indirmektir. Ekonomik sevk problemini çözmek için optimizasyon yöntemlerinin kullanılması, özellikle üretim birimlerinin yakıt maliyetini en aza indirgemek ve iletim kayıplarını azaltmak için sistem işlemlerinin maliyetini düşürmenin en uygun yoludur. Bu ekonomik işlem, bu işlemin verimliliği ve güvenilirliği göz önünde bulundurularak, her birim için asgari maliyete göre, tüm üretim birimleri arasındaki toplam yük talebinin paylaşılmasıyla sağlanmalıdır. Bu süreci kullanmanın temel amacı, sistem operasyonlarında fazladan para harcamasını önlemektir; buna karşılık, bu para kaydedilebilir. Ekonomik sevk problemi problemini çözmek için birçok optimizasyon yöntemi kullanıldı ve en son ve etkili algoritmalardan biri, bu yöntemin bu çalışmanın orijinali olan hybrid bat-crow search algoritması. Bu tezde, sistemin ekonomik güç dağıtımını çözmek için üretim birimlerinin bir kısmı için optimizasyon yöntemlerini kullanacağız. Bat algoritması, parçacık sürüsü optimizasyonu (PSO) ve genetik algoritma (GA) gibi en bilinen algoritmaları kullanacağız. Bu çalışmanın amacı güç dağıtım sistemlerinde ekonomik gönderim problemini ve birleşik ekonomik emisyon gönderim (CEED) problemlerini çözmektir. Önerilen hybrid bat-crow arama algoritması sonuçlarını, çeşitli güç sistemleri için bat, crow arama, GA ve PSO algoritmasıyla karşılaştıracağız. Güneş enerjisi için, Tripoli / Libya verilerini kullanarak Güneş Enerjisi ve Araştırma Çalışmaları Merkezi'ni kullanacağız. Aşağıdaki şekil, bu çalışmada kullanacağımız örnek güneş enerjisini göstermektedir..

Anahtar Kelimeler : Kombine Emisyon ve Ekonomik Sevk, Enerji Sistemi, Solar Foto Voltaik Üretim, Optimizasyon Yöntemi.

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ABBREVITIONS

CSA : Crow Search Algorithm
ED : Economic Dispatch
NO_x : Nitrogen Oxide
SO_x : Sulfur Oxide
CO_2 : Carbon Dioxide
CEED : Combined Economic Emission Dispatch
CPP : Conventional Power Plant
SPVPPs : Solar PV Power Plants
GHG : Greenhouse Gas
LPSP : Loss of Power Supply Probability
COE : Cost of Energy
REF : Renewable Energy Fraction
MOBA : Multi-Objective Bat Algorithm
FLC : Fuzzy Logic Control
ANN : Artificial Neural Network
EA : Evolutionary Algorithm
EP : Evolutionary Programming
TS : Tabu Search
GA : Genetic Algorithm
SA : Simulated Annealing
GSA : Gravitational Search Algorithm
PSO : Particle Swarm Optimization
BFA : Bacterial Foraging Algorithm
DE : Differential Evolution
GWA : Grey Wolf Algorithm
TLBO : Teaching-Learning-Based Optimization
HSA : Harmony Search Algorithm

SDE : Differential Evolution algorithms
EPD : Economic Power Dispatch
FA : Firefly Algorithm
LIM : Lambda-iteration method
DEIANT : Differential Evolution Immunized Ant Colony Optimization
DEIANT : Differential Evolution Immunized Ant Colony Optimization Technique
ACO : Ant Colony Optimization
PSO : Particle Swarm Optimization
PV : Photo Voltaic
MIOP : Mixed Integer Optimization Problem
ABC : Artificial Bee Colony
HRES : Hybrid Renewable Energy System
LCOE : Levelized Cost of Energy
AHP : Analytic Hierarchy Process
MCDA : Multi-Criteria Decision Analysis
LPSP : Loss of Probability of Power Supply
COE : Cost of Energy

CHAPTER 1

INTRODUCTION

1.1. HISTORY

The economic dispatch (ED) problem is of vital importance in the planning and running of power systems [1]. Its solution is extremely complex as it involves a nonlinear objective function and many constraints. In power systems, *ED* concerns establishing a schedule for the available generators allowing them to operate optimally in order to minimize the total cost of generation according to the systems' constraints [2][3]. Rising concerns over global warming have stimulated interest in reducing greenhouse gas (GHG) emissions, including those emitted during electricity generation from conventional sources like coal, oil, and natural gas. In addition, countries have been encouraged by energy security concerns to seek sustainable sources of energy in place of the diminishing fossil fuels. Renewable energy sources (RES) like the sun and wind are potential substitutes for generating power that are both sustainable and environmentally friendly. They involve, however, certain technical and economic problems preventing them from replacing the current sources used for power generation. *First*, they are unpredictable, sporadic, and unmanageable, and so they cannot be relied upon on their own to meet the load demand. Also, the technologies needed for utilizing *RES* are generally costlier compared to those used in conventional generators of comparable size, particularly when they are employed together with energy storage devices for higher reliability. Therefore, the price of the energy supplied is not competitive. *Finally*, they are difficult to integrate into the current centralized power generation and delivery infrastructures because they are distributed widely and dependent on location.

1.2. AIMS AND GOALS

The *ED* of power systems is an integral component of them and the main purpose of using it is to enable power system generation networks to operate reliably and efficiently, and this should be achieved by minimizing the generator fuel cost. Getting optimal solutions for the *ED* problem requires efficient optimization algorithms. The hybrid bat-crow search algorithm is one of the latest methods and it has already been proved efficient and reliable for solving this problem.

The objective of the research for this thesis was to formulate and implement a design strategy for determining the optimal configuration and operation plan for a *PV HPS* able to meet the energy needs of a grid-connected power distribution system, keeping the following considerations in mind:

- The design criteria are the annual system cost and CO_2 emissions. Total cost includes both capital (acquisition and installation) and operating (fuel, O&M, replacement . . . etc.) costs, while emissions include both direct (operational) and embedded emissions.
- *RES* are stochastic in nature.
- The technical and operational constraints of the system will not be violated by the solution, and a certain level of supply reliability will be ensured.
- The optimization model will be easy to apply and manage, and will yield results with a reasonable degree of accuracy.

In this thesis we propose the hybrid bat-crow search algorithm in order to solve the *ED* problem based on a large-scale power system that includes generation by solar photovoltaics.

1.3. SUBJECT, SCOPE

The hybrid bat-crow search algorithm is one of the most recent methods and it is already proving its efficiency and reliability for solving the *ED* problem. We propose to solve this problem using the hybrid algorithm, based on a large-scale power system involving solar photovoltaic generation. We will prove this algorithm is efficient and gives a perfect performance for small-scale systems. To test the performance of the algorithm for small- and large-scale power systems, we will apply it to the combined economic emission dispatch (CEED) problem.

1.4. CONTRIBUTION

The optimization of power system cost and protecting the atmosphere from being damaged by greenhouse gas (GHG) emissions are important, as are algorithms developed with these aims in mind. An algorithm suitable for these goals could help with effective active power scheduling, lowering both fuel costs and emissions from conventional fossil fuel-powered power plants at the same time [4]. This can also result in large financial gains [5] and cut harmful emissions of gases such as nitrogen oxide (NO_x), sulfur oxide (SO_x), and carbon dioxide (CO_2). Since these objectives are conflicting, multi-objective *CEED* issues may arise, which can be solved using traditional numerical programming processes such as gradient search and lambda iteration, or even by modern heuristic optimization methods. It is beneficial to solve such *CEED* issues using heuristic optimization methods instead of traditional population-based numerical programming methods. For searches that use stochastic operators, heuristic approaches do not require any mathematical data or gradient information. Furthermore, its implementation is both flexible and straightforward. They feature a parallel structural architecture that is inherently scalable and execute computations quickly [5].

This thesis explores the multi-objective optimization of the fuel cost of a conventional power plant (CPP) as well as the minimization of emissions in *CPPs* and solar *PV* power plants (SPVPPs) via a hybrid bat-crow search algorithm. To find a solution to this complicated, non-convex, and excessively nonlinear problem, various effective meta-heuristic optimization algorithms are formulated. To compensate for the shortcomings of evolutionary multi-objective algorithms, such as early convergence, slow meeting of the Pareto-optimal front, and narrow trapping, it is unusual to utilize a combination of diverse algorithms.

This thesis proposes hybrid evolutionary multi-objective optimization that combines the crow search optimization with the bat algorithm to tackle the *CEED* problem for *SPVPPs*. A hybrid technique in combination with the constriction handling method proposed can achieve balance between exploitation and exploration tasks. The proposed hybrid method was used to test different *IEEE* standard bus systems with the quadratic cost function and monitoring of transmission losses. The results obtained were compared with those of the bat, *PSO*, and crow search algorithms. The simulation results indicate that the proposed method is effective.

The *ED* of power systems is an integral part of them and the main reason for using it are to achieve the reliable and efficient operation of power system generation networks, and this should be achieved by minimizing the generator fuel cost. Getting optimal solutions for *ED* problems requires efficient optimization algorithms. The *PSO* algorithm is among the latest methods and it has already shown its efficiency and reliability in resolving the *ED* problem. In this thesis we propose the *PSO* Algorithm for solving the economic dispatch problem based on a large-scale power system involving solar photovoltaic generation. We will prove that the *PSO* algorithm is efficient and gives a perfect performance for small-scale systems. To test the performance of this algorithm for small- and large-scale power systems, we will apply it to *CEED* problem. The performance of grid hybrid frameworks is assessed depending principally on costs and reliability, associated with decreased *GHG* emissions of the system. In the present research, with the aim of minimizing two optimization features, i.e., loss of power supply probability (LPSP) and cost of energy (COE), the multi-objective optimization of a grid-connected *PV*/wind turbine framework was carried out at the Faculty of Engineering in Gharyan, Libya, while attempting to provide adequate electricity. Optimization of the system's renewable energy fraction (REF) was the third objective. It was also aimed to estimate the amount of power generated by the hybrid system and mathematical models were submitted. The results obtained revealed the proportion of the total energy meeting the demand for electricity in all parts of the network. Subsequently the interrelationship between the grid and the proposed hybrid system in relation to the capacity of the network to sell or obtain electricity from this system was examined. Furthermore, the findings from the multi-objective bat algorithm (MOBA) were split into three main areas: the economically optimal solution (lowest COE), the conceptual perspective of utilizing renewable energies (highest REF), and the optimal solution with optimal environmental effects (lowest GHG emissions).

1.5. THESIS ORGANIZATION

The rest of the thesis is organized as follows: *Chapter 2* includes the literature review. The methodology, research question, and goal functions are given in detail in *chapter 3*. The findings are discussed in *chapter 4*, while *chapter 5* contains the conclusions.

CHAPTER 2

LITERATURE REVIEW

2.1. INTRODUCTION

The optimization of power system costs and protection of the atmosphere from the damage caused by *GHG* emissions are vital, as are the algorithms developed for these aims. An algorithm suitable for these purposes may provide optimal active power scheduling to decrease both the fuel expenditures and emissions of conventional fossil fuel-powered power plants concurrently [4]. This may also allow large financial gains [5] and reduce emissions of dangerous gases including nitrogen oxide (NO_x), sulfur oxide (SO_x), and carbon dioxide (CO_2). Since these objectives are conflicting, multi-objective *CEED* issues may result, which can be tackled using traditional numerical programming processes such as gradient search and lambda iteration, or even by modern heuristic optimization. The resolution of these *CEED* issues will be advantageous if heuristic optimization methods are employed in place of traditional population-based numerical programming. No mathematical data or gradient information is necessary for heuristic searches. Stochastic operators are utilized for searches, and the method is flexible and simple to use. It involves an inherently scalable parallel structural design and performs calculations swiftly [5].

No single best result is achievable when such multi-objective *CEED* problems are being solved since there are conflicting objectives in these cases, namely reduced emissions and optimized fuel costs. Thus, these objectives are minimized concurrently to approach a transactional for multi-objective optimization. Further processing is necessary for a single favored outcome.

It is described in the literature how domination-based structures are employed via multi-objective evolutionary algorithms that decrease emissions and fuel costs when the *CEED* problem is being dealt with. Population-based approaches yield numerous non-dominant outcomes simultaneously [6]. These non-dominant outcomes indicate how emissions and fuel costs interact [7][8].

2.2. CONVENVENTIONAL METHODS

These methods comprise the gradient-based method [9], the lambda iteration method [10][11], linear programming [12], quadratic programming [13], and the Lagrangian multiplier method [14].

2.3. CLASSICAL TECHNIQUES

Classical techniques based on coordination equations [15] are employed to solve ELD problems. These conventional methods cannot satisfactorily solve such problems since they are sensitive to initial estimates and converge into a local optimal solution. Moreover, they are computationally complex.

2.4. FUZZY LOGIC CONTROL

In recent decades many studies and techniques have tackled *ELD* problems. Fuzzy logic control (FLC) has attracted interest for control applications. Unlike the conventional techniques, *FLC* devises the control action based on linguistic rules related to the behavior of a human operator instead of from an algorithm generated from a model of the system [16][17][18][19]. However, it needs more fine tuning and simulation before it is operational.

2.5. ARTIFICAL NEURAL NETWORK

There are both advantages and disadvantages inherent in the artificial neural network (ANN). The system’s characteristics are improved by *ANN*, but the technique’s foremost drawbacks include the long training time as well as selecting the number of layers and the number of neurons in each layer [20][21][22].

2.6. EVOLUTIONARY ALGORITHM

Another approach is evolutionary algorithm (EA) techniques. Based on its ability to deal with nonlinear objective functions, *EA* is thought to be very effective for solving the *ELD* problem.

The authors of [23] employed a simple novel indirect approach to track maximum power under rapid or gradual irradiation and temperature changes using a simple novel indirect algorithm. Simply put, every *EA* has its own qualities, and thus combination of the algorithms required is a natural way to tackle *CEED* issues. The integration of an *EA* with two or more optimization algorithms is termed hybridization.

M. F. Zaman et al. [24] employed two evolutionary algorithms to give the optimal generators' output according to the minimum fuel costs and solving the dynamic *EPD* problems. The self-adaptive differential evolution and real-coded *GA* were the algorithms recommended for a network. A diversity mechanism and constraint handling mechanism were used to improve the execution of the proposed algorithms. Using those techniques made the algorithm give better results in solving the dynamic *EPD*. In the future, these algorithms will be applied in solving the dynamic *EPD* problems, including renewable energy sources with thermal generation units.

2.7. EVOLUTIONARY PROGRAMMING

Evolutionary programming (EP) is examined in [25]; however, for large problems its convergence rate is slow.

2.8. TABU SEARCH

An improved tabu search (TS) is proposed in [26], but due to the use of highly epistatic objective functions and the numerous parameters to be optimized its efficiency is limited. Moreover, it is a time-consuming method.

2.9. GENETIV ALGORITHM

Another *EA* technique, *GA*, is described in [27][28]. However, a very long run time is required depending on the size of the system being studied. In addition, it results in the same suboptimal solutions being revisited continuously.

2.10. SIMULATED ANNEALING

Simulated annealing (SA) is explored in [29][30], but getting caught in a local optimal may lead to this technique's failure.

2.11. GRAVITATIONAL SEARCH ALGORITHM

The gravitational search algorithm (GSA) in described in [31]. While this algorithm seems effective for solving ELD problems, it performs poorly at the later search stage as a result of the limited agents' diversity.

2.12. META-HEURISTIC OPTIMIZATION ALGORITHMS

A number of meta-heuristic optimization algorithms are currently in use, such as *GAs* [32], *PSO* [33], scatter search (SS) [34], the bacterial foraging algorithm (BFA) [35], differential evolution (DE) [36], the grey wolf algorithm [37], teaching-learning-based optimization (TLBO) [38], the harmony search algorithm (HSA) [39], the hybrid big bang-big crunch algorithm [40], the glowworm swarm optimization algorithm [41], the "Blue Battery Concept for Energy Management of High Penetration of Renewable Energy Sources with Techno-Economic and Environmental Considerations" [42], [43] and the energy management concept for evolution of a smart grid [44], all of which are used to solve complicated, non-convex, and substantially nonlinear *CEED* problems. Multi-objective *CEED* problems can be converted into single-purpose problems by the application of a biased addition approach with the help of h parameter values, which assists in dealing with the dimensional issue when solving converted single and multiple objectives via evolutionary algorithms [38][39]. For resolving *CEED* problems without applying the h parameter, an alternative way is to regularize emissions and fuel costs. These approaches yield one objective solution at a time for the weights chosen. In [45] a renewable energy system was optimized using the *EMO*.

2.13. FIREFLY ALGORITHM

J. Merlin and Nagajothi [46] employed a developed firefly algorithm (FA) to resolve the *EPD* and minimize the expenditure of generating units. The proposed algorithm was applied to a dataset consisting of the *IEEE 30* bus system. Employing the *FA* was the best option to minimize these fuel costs and it gave better results than the other optimization methods, such as *GA* and *EP*.

Sreelekha and Scaria [47] employed the *FA* and self-adaptive differential Evolution (SDE) algorithm to reduce the power generators' costs by solving *EPD* for 10-generation units with valve point effect and multiple fuel equations for each unit. In short, the comparison between the results of both algorithms showed that the *FA* was capable of getting good quality optimal results when solving non-smooth *EPD* problems compared with the other algorithm.

Jaswant and Wadhwani [48] mainly used the *FA* to resolve the economic power dispatch (EPD) problem; also the lambda-iteration method (LIM) was applied for the same purpose. Both of them were applied to see which one will give the most optimal results in minimizing the fuel costs for the generation units. A virtual network was used, including 6 generation units, and the transmission line losses were considered in this work and also virtual data. As a result of this study, the results of the FA were more accurate and gave a more optimal solution than the other method (LIM).

2.14. ANT SWARM OPTIMIZATION

Ant swarm optimization is described in [49], but the theoretical analysis involved is complex and probability distribution changes with iteration.

2.15. ANT COLONY OPTIMIZATION

Rahmat et al. [50] utilized the differential evolution immunized ant colony optimization technique (DEIANT) in order to solve the *EPD* problems. The researchers got this algorithm by making improvement to the standard ant colony optimization (ACO) algorithm to get more accurate and efficient results of the power system. The objective was to determine the generators' output at the minimum fuel costs. Many constraints were calculated in this study, for example prohibited operating zones, valve loading effect, and ramp rate limits. Also, the transmission line losses were counted. These operational constraints made the system more complicated and non-linear. The results were obtained using *MATLAB*. The performance of the *DEIANT* algorithm was superior and accurate in reducing the generation units' fuel costs and in decreasing the losses.

Rahmat et al. [51] presented the *DEIANT* to solve the *EPD* problem and reduce the cost of electricity production for a power system, including prohibited operating zones. The intent of this study was to resolve the *EPD* problem for the power system economically and make the generation units operate according to the minimum fuel costs and with the same amount of power. The database includes the *IEEE 30* bus unit system. The proposed algorithm *DEIANT* was compared with the differential evolution (DE) and *ACO* algorithms. The numerical results were obtained using *MATLAB*. The proposed algorithm gave a good performance in solving the power system and the comparison indicated that the *DEIANT* algorithm was the best in term of minimizing the fuel costs of generation units.

2.16. PARTICLE SWARM OPTIMIZATION

Particle swarm optimization is examined in [52][53], but it suffers from partial optimism. Further, the algorithm is not able to solve scattering or optimization problems.

Naveed et al. [54] presented the combined emission economic dispatch of a power system involving solar photovoltaic generation based on the *PSO* method. They used

13 solar panels with *6* thermal units. They implemented their method in Egypt. In [54] *CEED* models were developed for a system including numerous photovoltaic (PV) plants and thermal units. They used the mixed integer optimization problem (MIOP). For solving the problem, they used *PSO*. In their scenario *13 PV* plants and *6* conventional ones are used.

2.17. ARTIFICAL BEE COLONY

In [55] the artificial bee colony (ABC) was used to solve the complex non-linear optimization problem, but its convergence is slow and the exploration and exploitation processes conflict with each other. Therefore, to achieve good optimization, good balance should be ensured between the two abilities.

Rahmat et al. [51] used the *DEIANT* to solve the *ED* problem. They used the *IEEE 30-Bus* reliable test system.

2.18. HYBRID METHODS

Emmanuel et al. [56] used *ABC* combined with *PSO* for multi-objective environmental/economic dispatch solution. They used the *30-bus* with *6* generator *IEEE* standard.

Raul et al. [57] used *PSO* and *GA* together to solve the *ED* problem. The mutation operation was used to explore the region in the search area of the *PSO* method.
Barros et al. [58] applied a hybrid algorithm based on *PSO* and *GAs* for solving the problem of *ED*. They based their method on the demand for energy that reaches a low cost. The mutation operation from the *GA* is used to explore regions of the search area in this scenario by the canonical version of the *PSO* method. They used *3* scenarios with *3*, *13*, and *20* generators.

Elyas et al. [59] described a new hybrid optimization algorithm based on the clonal selection algorithm (CSA). Their method combines the positive features of two other optimization techniques, namely gases Brownian motion optimization (GBMO) and *PSO*, in local searches.

In previous research [60] the successful use of hybrid algorithms was demonstrated for solving *CEED* problems as well as a number of other composite engineering issues and test functions. Broadly speaking, the outcomes show that these hybrid algorithms are useful and are able to exchange the hybrid structure’s elite information, and are employed in parallel processing, exploring, and exploiting potential with a better performance than a single algorithm. A transaction is required between tasks such as exploitation and exploration in order to guarantee an internationally recognized best solution. In all algorithms, the exploration phase is critical for locating the solution area and estimating the global optimal point. When looking for outstanding solutions through neighborhood searches, it's also important to use an algorithm. [60]. As explained in [61], solar energy was employed in vehicle systems.

The present thesis explores the bat algorithm in combination with the crow search algorithm [62] to solve the *CEED* problem for a hybrid structure because when combined the useful features of the two algorithms are obtained and their individual flaws are restricted. In population-based techniques like these, different procedures are utilized to explore the space and integrate in order to enhance the transaction between exploitation and exploration for obtaining high quality solutions. A major reason for this hybridization is to obtain a diverse and fully distributed objective solution. We spoke about how the *CEED* problem is formulated and how transmission losses and limitations are handled. The relevant hybrid, crow search, and bat algorithms were then examined. The outcomes of applying the hybrid method to various standard *IEEE* bus systems were evaluated. Hybrid optimization methods outperform single optimization methods; additionally, as evidenced by the data, our hybrid method was just as successful as the bat-crow search algorithm.

When solving such multi-objective *CEED* problems, a single optimal result is not possible because in these cases the objectives are conflicting, namely emission reduction and fuel cost optimization. Thus, these objectives are minimized concurrently to approach a transactional for multi-objective optimization. Further processing is necessary for a single favored outcome to be obtained. The literature describes dominance-based architectures that use multi-objective evolutionary algorithms to reduce pollution and fuel costs while tackling the *CEED* challenge.

2.19. OTHER METHODS

As the demand for electricity continues to rise and conventional energy resources are being depleted rapidly, the search for renewable energies as alternative energy sources has become crucial. *PV* solar and wind power are considered the most viable sources of electricity as the market for power from multiple clean energy sources continues to grow. Furthermore, the current penetration rates of *PV* systems are high, and the use of *PV* cells and advanced electronic technologies is predicted to grow worldwide. In addition, wind power is regarded as the most important form of renewable energy due to its efficiency, ubiquity, and high capacity. However, there is not yet full confidence in wind and *PV* energy and they involve some disadvantages, including being vulnerable to unpredicted natural conditions and being hugely dependent on variations in environmental conditions like sunlight and wind speed. Therefore, *PV* energy and wind energy combined may make up for individual variances in *PV* and wind hybrid power generation networks, increase overall power capacity, and be more efficient, which means better quality electricity is supplied to the grid [63], [64], [65], [66].

In mountainous and rural regions where systems might be set up near demand areas, renewable energy has been shown to be the best solution for micro-networks, thus making traditional electricity grids unnecessary [67]–[70]. Similarly, on-grid and off-grid renewable energy frameworks have been constructed. Generally, the issue concerning the potential use of renewable energy sources is resolved by many different energy supplies that are wholly dependent on unpredictable environmental conditions and that are not completely specified in terms of their energy output. For instance, while wind and solar energy are generally used in combination, a more stable energy source, such as biomass energy, can be used to ensure that constant production of energy is obtained using such hybrid combinations that is more predictable and stable [71–77].

The sizing of a hybrid renewable energy system (HRES) is complicated due to the unpredictability of renewable resources, and it is important to maintain a balance between economic aspects and reliability. As a result, many models, algorithms, and software tools have been employed for the optimization of *HRES* frameworks. They include Tiryns, Rescreen and *PVSOL*, *Hybrid2*, *TRANSYS*, *SAMS*, and *RAPSYS*, as well as *HOMER* (Hybrid Optimization of Multiple Energy Resources) [78-79]. These tools generally are still commonly used for checking optimized outcomes based on energy costs and the technical integration of elements of the infrastructure including wind turbines, solar modules, and inverters, with relation to controllers and power storage [80-81].

There are easily available software solutions for the optimization of *HRESs* [78], and when it comes to system modification no user-defined constraints are needed for the associated configuration and size processes. Moreover, mathematical models and algorithms are often used in the current *HRES* design process to alleviate the drawbacks.

In [82] and [83], *HOMER Pro* used a combination of technical, environmental, and related economic domains to develop a policy application system for effectively planning and appraising hybrid microgrid-based systems based on renewable energy. Further, for establishing how to best combine diverse subsystems in terms of technological, environmental, and financial efficiency, net present value (NPV) was found to be the most dependent parameter for hybrid microgrids based on renewable energy. Consequently, system configurations were determined using the total cost of life cycles, also known as the *NPV*. *HOMER* was also used in [84] and [85], in which configurations of technically feasible and eco-friendly distributed energy systems were examined based on the annualized overall cost, which is connected to the levelized cost of energy (LCOE).

For *HRESs* the current method is still optimization with respect to the use of metaheuristic implementation using algorithms for design as well as sizing. Among the algorithms that exist, the bat optimization algorithm [85], crow search algorithm [86], *PSO*, evolutionary metaheuristic algorithm, computational annealing, differential evolution, and cuckoo scan are the most common metaheuristic ones.

In [87], the resilience of a microgrid for assisting in decision-making was determined using five main parameters: technological, social, cultural, political/institutional, and climate factors. Likewise, the analytic hierarchy process (AHP) [88], which is objective, has been employed to find the values of requirements for optimal hybrid systems. Further, in [89][90], renewable energy was integrated into the grid by using multi-criteria decision analysis (MCDA), which appraises the technical and financial optimization of seasonal change to yield the optimum configuration for the *AHP* application framework. The principal aim in the present thesis is to define the optimal number and types of components in a hybrid grid network, keeping both financial and environmental issues in mind. It was also aimed to improve the *MOBA* by using actual hourly electricity information from the Faculty of Engineering in Gharyan, Libya, through testing to decrease the objective attributes of loss of probability of power supply (LPSP), process cost of energy (COE), and environmental effects (reduction of GHGs).

CHAPTER 3

MATERIALS AND METHODS

3.1. BACKGROUND

In computer science, a problem-solving technique is intuitive or heuristic. It doesn't matter if the result is provable or not, but it usually gets close to good solutions. Heuristic algorithms, on the other hand, are algorithms that reduce the solution time by giving up searching for the best solution in order to become more efficient in the transition time. Heuristic algorithms do not guarantee that they will find the best solution, but they do guarantee that they will find a solution within a reasonable time. They usually reach the solution that is close to the best quickly and easily. As an example of heuristic search algorithms.

A* search (A star)
Beam search
Hill climbing algorithm
Best first search
Greedy best first search
Simulated Annealing algorithm
Backtracking
In other words, heuristic algorithms are known as functions that calculate the cost of the shortest path from one node to another.

3.2. HEURISTIC OPTIMIZATION

Heuristic algorithms can provide near-optimal solutions when optimizing large-scale problems within a reasonable time. General purpose heuristic optimization algorithms are divided into six different groups: those based on biology, physics, herds, society, music, and chemistry. Swarm intelligence-based optimization algorithms have been formulated based on the movements of swarms of animals such as birds, fish, cats, and bees [1].

Examples of heuristic optimization methods:

Genetic Algorithm (GA)
Ant Colony Optimization (ACO)
Particle Swarm Optimization (PSO)
Artificial Bee Colony (ABC)
Differential Evolution Algorithm (DEA)
Simulated Annealing (SA)
Gravity Search Algorithm (GSA)
Gases Brownian Motion Optimization (GBMO)
Heat transfer search (HTS)
Electromagnetic Field Optimization (EFO)
Optical Inspired Optimization (OIO)
Weighted Superposition Attraction (WSA)
Forest Optimization Algorithm (FOA)
Hurricane Based Optimization Algorithm
Black Hole Optimization Algorithm
Water Cycle Optimization Algorithm
Fruit Fly Optimization Algorithm
Krill Swarm Optimization Algorithm
Bacterial Foraging Behavior
Bat Algorithm
Firefly Algorithm
Lion Algorithm
Gray Wolf Algorithm
Dolphin Algorithm
Bush Colony Algorithm
Artificial Algae Algorithm
Virus Colony Search Algorithm

Shark Smell Optimization Algorithm

Social Spider Algorithm

Tree-Seed Algorithm (TSA)

Taboo search algorithm

3.3. PROPOSED METHOD BASED BASED ON A HBRID METHODS

The bat-crow search algorithm is simple to implement and finds the optimum solution quickly. Furthermore, it ensures escape from the local minimum solution. Thus, this algorithm is presented herein to surmount the disadvantages previously seen. Moreover, a literature survey clearly shows that use of the bat-crow search algorithm has not been proposed for solving the *CEED* problems of power systems including solar *PV* generation. This prompted us to use this algorithm to deal with these problems. Also, in this thesis solar energy was used. We employed optimization methods for a part of the generating units in order to solve the economic power dispatch for the system. We employed the best known algorithms, such as the bat algorithm, *PSO*, and *GA*. Figure 3.1 shows the sample solar energy that we used in this study.

Figure 3.1. Solar panels in Libya.

Also for confirming the result the following data are used (see Table 3.1):

Table 3.1. Data and the information.

Time	**Global solar radiation (W/m^2)**	**Power demand (MW)**	**Temperature (°C)**
1	0	978	24
2	0	1156	23.6
3	1	1205	22.8
4	1	1209	23.2
5	8	1176	23.5
6	103	1156	22.7
7	293.7	1160	23
8	581.2	1083	23.6
9	590.4	1175	28.2
10	893.9	1274	32.8
11	1067	1148	33.1
12	1134	1274	34
13	1035	1178	35.2
14	878	1334	36
15	756	1085	36.3
16	673	1206	37.2
17	422.9	1287	31
18	360	1179	29
19	107	1354	27.9
20	30	1358	26.3
21	1	1278	26
22	1	1175	25.5
23	0	1226	24.5
0	0	1312	23.8

For the global solar radiation (W/m^2) the result is shown in Figure 3.2.

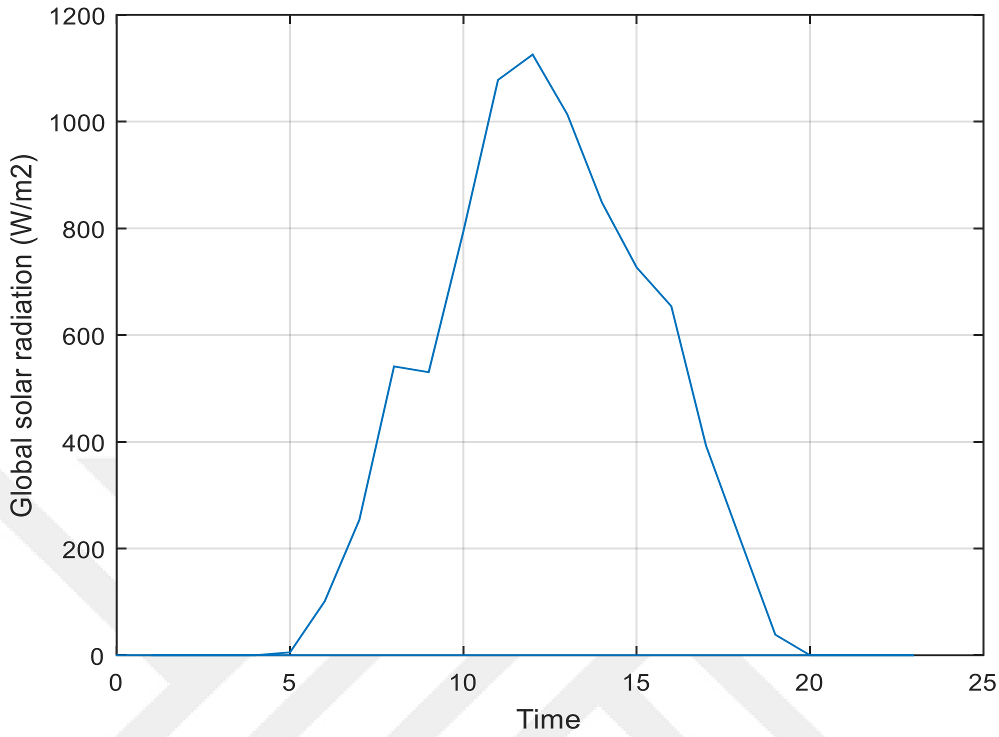


Figure 3.2. Global solar radiation (W/m^2).

For the fuel cost coefficients and generating capacities of the thermal generating units the following data are used (see Table 3.2); these data are from [91].

Table 3.2. Fuel cost coefficients and generating capacities of thermal generating units.

Machine no.	*a* (\$/MW^2 h)	*B* (\$/MW h)	*c* (\$/h)	P_{min} (MW)	P_{max} (MW)
1	0.15251	38.49932	757.80344	11	126
2	0.10603	46.16023	451.31567	11	151
3	0.02834	41.00341	1050.31456	41	251
4	0.03576	38.29654	1256.5432	36	211
5	0.02209	36.33005	1660.5687	131	326
6	0.01803	38.28345	1359.29322	126	316

3.4. METHOD

3.4.1. Mathematical Modeling

The *ED* problem that can be found in thermal power and solar PV generators is described in this article. A static or dynamic model can be used to create *ED* challenges in general. Both case studies were completed, and the numerical model for each is shown below.

3.4.1.1. Solar Power with CEED

The environmental and *ED* problem may be regarded as a multi-objective functional problem, and it is more commonly referred to as *CEED*. The numerical model for this problem is the following:

$$minG = \sum_{i=1}^{n}(F_i(P_i) + E_i(P_i)), \tag{3.1}$$

where $F_i\ (P_i)$ represents the fuel cost of the ith generation unit and $E_i(P_i)$ the emissions of the ith generating unit, and G is a problem minimization function with the following constraints:

$$\left(\sum_{i=1}^{n} P_i\right) - P_L - P_d = 0, \tag{3.2}$$

where P_L is the transmission losses, P_d is power system demand, n is the power generating units, and P_i is the generated power of the i^{th} unit. The inequality constraint is

$$P_{imin} \leq P_i \leq P_{imax} \tag{3.3}$$

P_{imin} and P_{imax} represent the lower and upper power generation limits of the i^{th} generation unit, respectively. The following equation includes emission cost, fuel cost, and transmission losses:

$$F_i(P_i) = a_iP_i^2 + b_iP_i + c_i + |e_i * sin(f_i * (P_{imin} - P_i))| \$/h \tag{3.4}$$

The fuel cost coefficients are shown by a_i, b_i, c_i, e_i, and f_i for the i^{th} unit generation.

$$E_i(P_i) = \alpha_iP_i^2 + \beta_iP_i + \gamma_i + \varepsilon_i * exp(\delta_i * P_i) Kg/h \tag{3.5}$$

The emission cost coefficients are expressed by α_i, β_i, γ_i, ε_i, and δ_i for the i^{th} unit generation. The losses occurring in the transmission line are determined via the following equation, where B is the losses coefficient for the transmission-line equation:

$$P_L = \sum_{i=1}^{n} \sum_{j=1}^{n} P_iB_{ij}P_j \tag{3.6}$$

The penalty factor (hi) and the multi-problem objective function for emission and cost dispatches are as follows:

$$Min\ F_c = \sum_{i=1}^{n}\Big(a_iP_i^2 + b_iP_i + c_i + \big|e_i * \sin\big(f_i * (P_{imin} - P_i)\big)\big| + h_i(\alpha_iP_i^2 + \beta_iP_i + \gamma_i + \varepsilon_i * \exp(\delta_i * P_i))\Big)\frac{\$}{h} \tag{3.7}$$

The penalty factor h_i is determined as follows:

$$h_i = \frac{a_iP_{imax}^2 + b_iP_{imax} + c_i + |e_i * \sin(f_i * (P_{imin} - P_{imax}))|}{\propto_i P_{imax}^2 + \beta_iP_{imax} + \gamma_i + \varepsilon_i * \exp(\delta_i * P_{imax})} \tag{3.8}$$

Solar PV power generation is calculated using

$$P_{gs} = P_{rated}\{1 + \left(T_{ref} - T_{amb}\right) * \propto\} * \frac{S_i}{1000}, \tag{3.9}$$

where P_{rated} is the nominal power of the solar PV power plant (SPVPP), T_{ref} is the temperature reference for the SPVPP, T_{amb} is the environment's ambient temperature, and S_i is the solar incident radiation. The scheduled sharing of solar *PV* power is computed as follows if *m* SPVPPs are available in the system for fulfilling demand and sharing the *SPVPP* system:

$$Solar\ share = \sum_{j=1}^{m} Pgs_j \times Us_j \tag{3.10}$$

P_{gsj} is the accessible power level of the j^{th} *SPVPP* and U_{sj} is the *ON (1)* or *OFF (0)* state of the j^{th} SPVPP. The solar power cost is determined by

$$Solar\ cost = \sum_{j=1}^{m} PUCost_j \times Pgs_j \times Us_j \tag{3.11}$$

$PUCost_j$ is the per unit cost of the j^{th} *SPVPP*. The objective for the static dispatch (cost and emission) with the *SPVPP*, which is the first major point of the present study, is given as follows:

$$Min\ F_T = \sum_{i=1}^{n}\Big(a_iP_i^2 + b_iP_i + c_i + \big|e_i * \sin\big(f_i * (P_{imin} - P_i)\big)\big| + h_i(\alpha_iP_i^2 + \beta_iP_i + \gamma_i + \varepsilon_i * \exp(\delta_i * P_i))\Big) + \sum_{j=1}^{m} PUCost_j \times Pgs_j \times Us_j + Ks\Big(\sum_{j=1}^{m} Pgs_j - \sum_{j=1}^{m} Pgs_j \times Us_j\Big) \tag{3.12}$$

The second major point of this research is the goal for dynamic dispatch (emission and economy) with the *SPVPP*, which is as follows:

$$Min\ F_T = \sum_{t=1}^{N}\sum_{i=1}^{n}\left(a_i(P_i^t)^2 + b_iP_i^t + c_i + \left|e_i * \sin\left(f_i * (P_{imin} - P_i^t)\right)\right| + h_i(\alpha_i(P_i^t)^2 + \beta_iP_i^t + \gamma_i + \varepsilon_i * \exp(\delta_i * P_i^t))\right) + \sum_{j=1}^{m} PUCost_j \times Pgs_j \times Us_j^t + Ks\Big(\sum_{j=1}^{m} Pgs_j^t - \sum_{j=1}^{m} Pgs_j^t \times Us_j^t\Big) \tag{3.13}$$

3.5. ALGORITHMS USED FOR MODELING

3.5.1. Principles of the PSO Algorithm

In 1995 Kennedy and Eberhart reported a new approach for the optimization of particle swarms. They were inspired by the social behaviors of groups such as birds, fish, and ants. Their algorithm emulates the exchange of information between members. *PSO* has been applied for optimization alone and combined with other algorithms in various areas. The algorithm searches for the optimum solution via agents, called particles, whose trajectories are modified by a stochastic and deterministic component. Every particle is affected by its “best” position and the “best” position achieved in the group, but they usually shift randomly. Particle position and velocity are determined by the following equations [92]. The best particle position is shown by *xBest* and the global particle position by *gBest*, inertia weight is shown by ω, positive constants are shown by c_1 and c_2, and random variables between 0 and 1 are shown by r_1 and r_2, respectively. In every iteration the velocity and particle position are altered in order to minimize or maximize the problem being examined.

$$v_i^{t+1} = wv_i^t + c_1r_1(xBest_i^t - x_i^t) + c_2r_2(gBest_i^t - x_i^t) \tag{3.14}$$

$$x_i^{t+1} = x_i^t + v_i^t.t \tag{3.15}$$

3.5.2. Fundamentals of the Bat Algorithm

Yang created this meta-heuristic optimization algorithm in 2010, which is currently among the best [93]. Bats are winged mammals that have the ability to determine location and direction by echolocation using reflected sounds. This is a sonar technique that bats use it to find their prey and to avoid hitting obstacles in the dark. They emit short high frequency sounds and receive echoes from the objects around them. This technique enables bats to know the sizes, shapes, distances, motions, and directions of objects. The bat algorithm is based on the echolocation mechanism of bats and it is shown mathematically as follows:

Movement of a bat:

$$\begin{gathered} f_i = f_{min} - f_{max} \\ V_i^t = V_i^{t-1} + (X_i^t - X^*)f_i * rand \end{gathered} \tag{3.16}$$

$$X_i^t = X_i^{t-1} + V_i^t \tag{3.17}$$

As β is between *0* and *1*,

$$X_{new} = X_{old} + \varepsilon A^t \tag{3.18}$$

Here ε is between *-1* and *1*, and it is a random number at a specific time t. It represents the average loudness of all bats; thus, $A^t = \langle A_i^t \rangle$.

Pulse emission and loudness:

$$A_i^{t+1} = \alpha A_i^t \tag{3.19}$$

$$r_i^{t+1} = r_i^0 [1 - exp(-\gamma t)], \tag{3.20}$$

where α and γ are constants.

The initial bat algorithm did not take into account the effect of Doppler shifts or the principles of bats' foraging behavior, with each bat being expressed in terms of position and velocity, hunting prey in the dimensional spaces according to the trajectory achieved. This should not be treated in isolation though. The Doppler effect should be considered in the bat algorithm, and bats show successful adaption to the Doppler effect, which explains how echoes work [93].

Simply put, a bat has habitats where it forages, and these are diverse in the bat algorithm. It searches for food in a single habitat in this algorithm due to the virtual bat's mechanical behavior. To sum up, the bat algorithm must take the following idealized basics into consideration:

- Bats move in various habitats.
- Bats are able to adapt to the Doppler effect in echoes.
- Bats acclimate and establish compensation averages based on the proximity of the target [93].

3.5.2.1. Quantum Behavior

The assumption is that when one bat in a group finds prey in a specific habitat, the other bats will instantly start to feed on the same prey. This is the mathematical basis for the following formulation of bat positions [93]:

$$X_{i,j}^{t+1} = \begin{cases} g_j^t + \theta * \left| mean_j^t - X_{i,j}^t \right| * \ln(\frac{1}{u_{i,j}}), if rand_j(0,1) < 0.5 \\ g_j^t - \theta * \left| mean_j^t - X_{i,j}^t \right| * \ln(\frac{1}{u_{i,j}}), if rand_j(0,1) > 0.5 \end{cases} \quad (3.21)$$

3.5.2.2. Mechanical Behavior

In addition, it is assumed that a virtual bat's velocity will not be greater than the speed of the sound, estimated to be *340 m/s*. The bat will make allowance for the Doppler effect, and this will be expressed mathematically as *CR* as it differs between different bats. *CR* and the inertia weight *w* take values from *0* to *1*. The ξ value expresses the smallest constant for avoiding the probability of division by *0*. *CR* will be *0* if the bat's Doppler effect is not compensated for and will be *1* if it is. This can be expressed mathematically as shown below [93]:

$$f_{i,j} = f_{min} - f_{max} \quad (3.22)$$

$$f_{i,j} = \frac{c+v_{i,j}^t}{c+v_{g,j}^t} * f_{i,j} \; * \; (1 + CR_i * \frac{g_j^t - X_{i,j}^t}{\left|g_j^t - X_{i,j}^t\right| + \xi} \quad (3.23)$$

$$V_{i,j}^{t+1} = w * V_{i,j}^t + (g_j^t - X_{i,j}^t) * f_{i,j} \quad (3.24)$$

$$X_{i,j}^{t+1} = X_{i,j}^t + V_{i,j}^t \quad (3.25)$$

3.5.2.3. Local Search

It is logically assumed that the sound volume will be reduced, and the pulse emission rate will be increased as bats approach their prey. Regardless of the loudness value used, calculations of the loudness factor should be based on the environment. This is expressed in the following equations [93] If (rand (0, 1) >ri), where rand *n* (0,$\boldsymbol{\sigma^2}$) shows the Gaussian distribution with mean value *0*, $\boldsymbol{\sigma^2}$is the standard deviation, and $\boldsymbol{A_{mean}^t}$ is the arithmetic mean of loudness.

$$X_{i,j}^{t+1} = g_j^t * (1 + randn(0, \sigma^2)) \tag{3.26}$$

$$\sigma^2 = |A_i^t - A_{mean}^t| + \xi \tag{3.27}$$

3.5.3. Crow Search Algorithm

The crow search algorithm, developed by Askarzadeh [94], mimics the behavior of a crow when looking for food and sharing the location and type of food with another crow; it is regarded as one of the world's most intelligent animals by some people [95]. Its behaviors are useful in terms of heuristics. This algorithm is based on the activities for acquiring food that crows constantly engage in, which include the hiding of food and communication with another crow in order to enable the stealing of food. The crow's behavior also includes random movements to mislead a rival or to protect food from other crows [96].

3.5.4. Hybrid Bat-Crow Search Algorithm

The emission cost, fuel cost optimization, and *SPVPPs* required for *ED* using the new hybrid bat-crow algorithm are explained here. The bat algorithm obtains the global maximum/minimum value in order to solve a problem. In comparison with the bat algorithm, faster convergence rates are achieved with the crow search algorithm.

The flowchart in Figure 3.3 for the hybrid of the two algorithms involves different parameters, including the number of generations, initial population, loudness, frequency, bat pulse rate, and speed of the bat during flight.

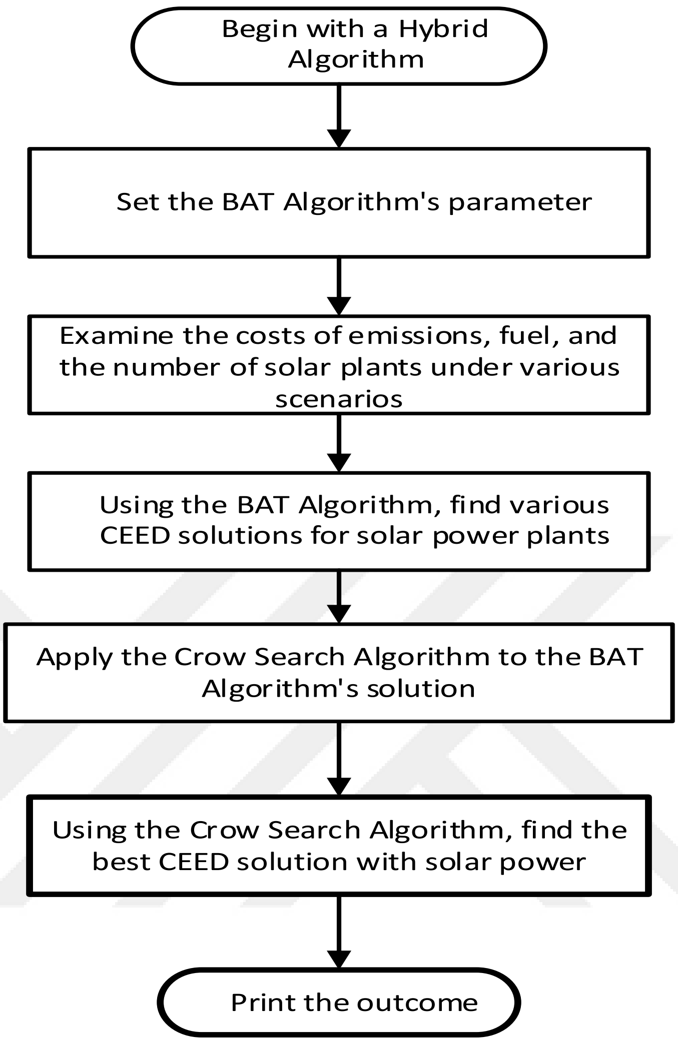


Figure 3.3. Flowchart of the Hybrid Bat-Crow Search Algorithm.

In the crow search algorithm for flight length, which also considers awareness probability, the fuel cost, emission cost, and number of *SPVPPs* are read when, for the initial population, the bat algorithm is used with a variety of operating conditions when seeking different solutions.

The specific initial population of the crow search algorithm helps us to solve the bat algorithm. The bat algorithm has the following parameters: maximum frequency of *2*, minimum frequency of *0*, pulse rate of *0.1*, loudness factor of *0.2*, and number or population size of *100*, while the crow search algorithm has the parameters awareness probability of *0.01*, flight length of *2*, and number or population size of *100*.

The application framework's energy management strategy is described here along with details of the components of mathematical platform models needed for the proposed application framework, as well as estimates of *GHGs* and definitions of the objective functions. The reduced calculation of the energy costs via the system was based on the lifespan of the project as well as various elements through reduced cash flow analysis. The required life cycle of the *PV* devices, wind turbines, and battery banks was assumed to be (20,15) as well as *20* years [97], with a project lifespan of *20* years. Furthermore, the precision of the estimates is enhanced using measurements via the economic factors of interest rate (I_r) and inflation rate (I_f). A schematic of the *PV*-wind turbine-battery on-grid system is shown in Figure 3.4.

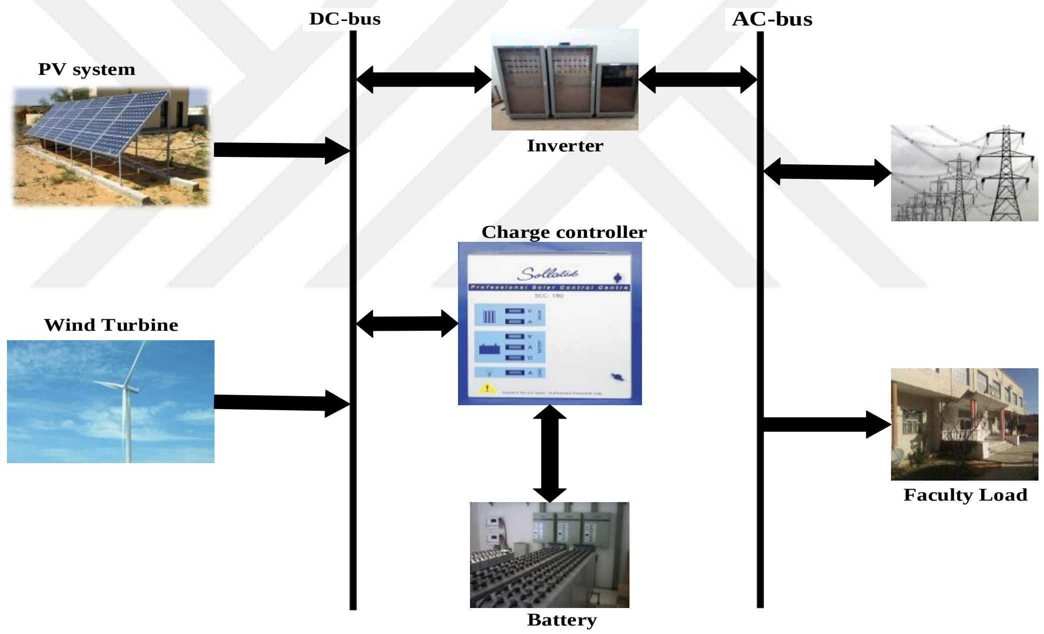


Figure 3.4. A schematic representation of the PV-wind turbine-battery on-grid system.

3.6. PV SYSTEM

The optimization algorithm's main purpose is to determine the optimum number of systems using a full solar-PV framework comprising *sixty-two 250-W* solar panels, connected to a *15-kW* inverter.

The production power of the PV generator in a year can by calculated using the following equation:

$$P_{pv} = \sum_{t=1}^{T}(P_{PVr} \times N_{pv} \times DF_{pv})\left(\frac{G\,(t)}{G_{base}}\right)\left(1 + K_T\left((T_{amb}(t) + G(t) \times \left(\frac{NOCT-20}{800}\right) * 1000\right) - T_{base})\right)\ , T = 8760 \tag{3.28}$$

The total net present cost NPC_{pv} is based on original costs IC_{pv} as well as operational and repair costs $O\&MC_{pv}$. Since the lifespan of the device matches that of the project, no replacement costs are incurred. Thus, NPC_{pv} is calculated as follows [98][99]:

$$NPC_{pv} = IC_{pv} + O\&MC_{pv} = N_{pv} \times \left[IPR_{pv} + \sum_{n=0}^{20}\frac{OMP_{pv}}{\left(1+\frac{I_r-I_f}{1+I_f}\right)^{n-1}}\right] \tag{3.29}$$

All the necessary information was recorded on an hourly basis. The solar radiation and weather temperature profiles for the *year 2020* are shown in Figures 3.5 and 3.6, respectively.

Figure 3.5. Global solar radiation in 2020.

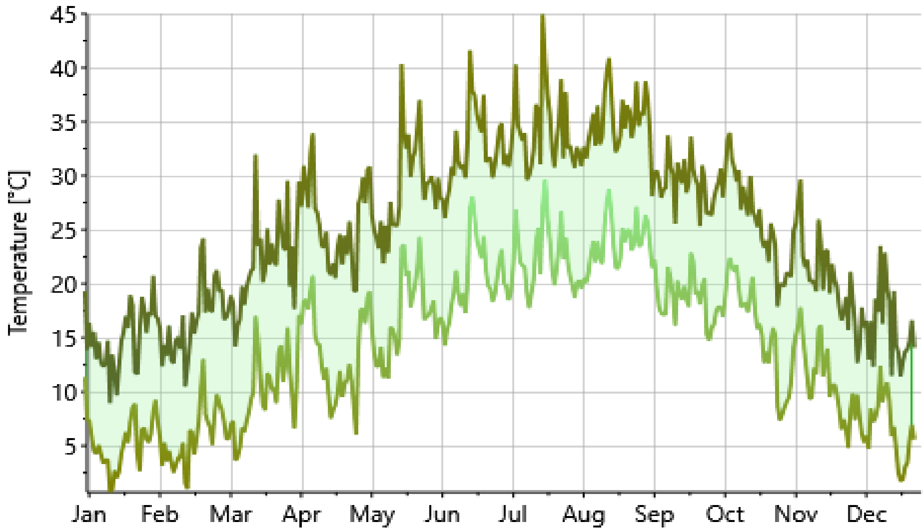


Figure 3.6. Weather temperature profile for 2020.

3.7. WIND TURBINE SYSTEM

The production capacity of wind turbine generators is mainly dependent on wind speed. The following equation is used to determine the output power of a wind turbine over one year [100]:

$$P_{WT} = \begin{cases} N_{WT} \times \eta_w \times P_{WTr} \times \sum_{t=1}^{T} \left(\frac{V(t)^3 - V_{ci}^3}{V_r^3 - V_{ci}^3} \right), & V \leq V_r \\ N_{WT} \times \eta_w \times P_{WTr}, & V_r \leq V \leq V_{CO} \\ 0, & V_{CO} \leq V \text{ or } V \leq V_{ci} \end{cases}, T = 8760 \quad (3.30)$$

$V(t)$ represents the wind speed of the blades (m/s) at the hub height:

$$V(t) = V_r \left(\frac{H_{WT}}{H_r} \right)^{\propto} \quad (3.31)$$

H_{WT} is the height of the wind turbine hub, while H_r is the reference height, which is related to (α), the coefficient of friction, which is normally employed with low surface ruggedness and exposed spots [101], [102].

As the lifetime of the wind turbine is 15 years, replacement is necessary every 15 years. Further, the net cost of the wind turbine method is gauged by the following equation:

$$NPC_{WT} = IC_{WT} + RC_{WT} + O\&MC_{WT} = N_{WT} \times \left[IPR_{WT} + \frac{RP_{WT}}{\left(1+\frac{I_r - I_f}{1+t_f}\right)^{15}} + \sum_{n=0}^{20} \frac{OMP_{WT}}{\left(1+\frac{I_r - I_f}{1+t_f}\right)^{n-1}} \right] \quad (3.32)$$

The mean wind speed profile for *2020* is shown in Figure 3.7.

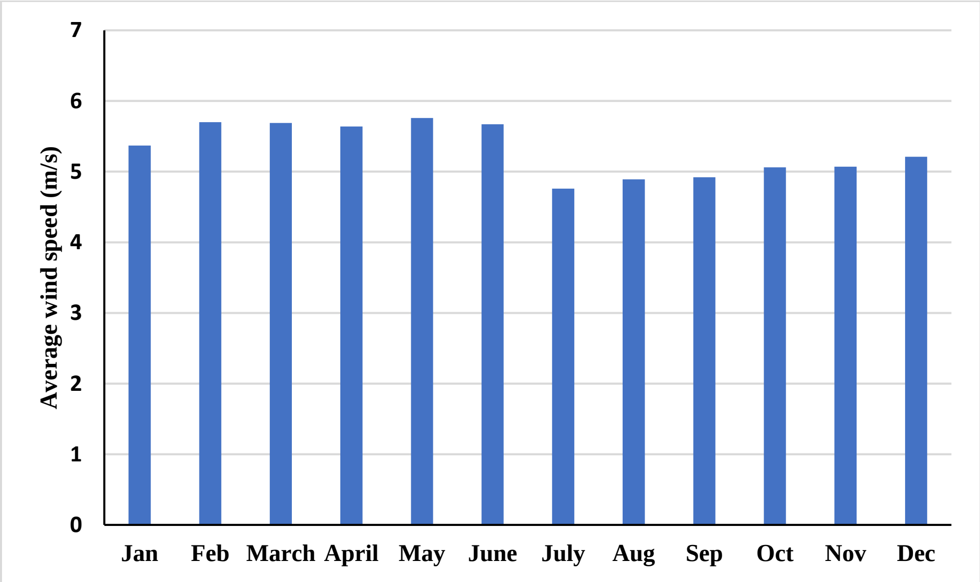


Figure 3.7. Mean monthly wind speed for 2020.

3.8. BATTERY SYSTEM MODELING

The surplus capacity of the system is stored in batteries for use whenever necessary. Battery energy storage involves the following restrictions:

$$E_{Bat,min} \leq E_{Bat}(t) \leq E_{Bat.max} \quad (3.33)$$

$$E_{Bat,max} = E_{Bat.cap} \quad (3.34)$$

$$E_{Bat,min} = E_{Bat.max}(1 - DOD) \quad (3.35)$$

Battery charging and discharging are determined as follows [81], [103]:

$$C(t) = C(t-1)(1-\sigma) + (surplus\,power)\eta_b \tag{3.36}$$

$$C(t) = C(t-1)(1-\sigma) - (deficit\,power) \tag{3.37}$$

The battery discharge output is kept at *1* during discharge.

In the experimental project we implemented, the usable battery energy is *18.4 kWh*, with a total of *300 Ah*, a *24-kWh* nickel-iron (Ni-Fe) battery bank with *80% DOD*, and *1%* self-discharge every *24 hours*. The lifespan of the battery bank is *20 years* and so during the project there are no replacement costs. The net present cost of the battery bank is determined by the following equation:

$$NPC_{BAT} = IC_{BAT} + O\&MC_{BAT} = N_{BAT} \times \left[IPR_{BAT} + \sum_{n=0}^{20} \frac{OMP_{BAT}}{\left(1+\frac{I_r - I_f}{1+t_f}\right)^{n-1}} \right] \tag{3.38}$$

3.9. GRID SYSTEM

Grids are energy sources capable of absorbing energy and modeling an infinite source. Herein a grid is used to make up any lack of power if the *PV* or wind turbine device is unable to provide the electrical charge necessary for the Faculty of Engineering and if the batteries do not make up for the electricity shortfall. The income generated by sales of resources to the utility is determined as follows:

$$R_{grid} = \sum_{t=1}^{8760} rate_{feed-in}.\, E_{grid_{selling}} \tag{3.39}$$

Here $rate_{feed-in}$ represents the feed-in tariff rate of *0.05 $/kWh*.

The cost incurred when buying power from the grid is computed by

$$C_{grid} = C_p \times \sum_{t=1}^{8760} E_{grid_{purchased}} \tag{3.40}$$

Here C_p is the cost of purchasing *1 kW* from the grid in Libya, which is equal to *$0.04/kWh*.

3.10. ESTIMATION OF GHG EMISSIONS

GHG emissions are calculated for the *PV* system, wind turbines, and grid. The results found in the present study were also used for implementation of the planned program to meet the needs of the Faculty of Engineering and to determine the cumulative volume of the net reduction in *GHG* emissions in Gharyan via renewable energy. *GHG* emissions are specifically assessed herein solely for meeting the needs of the Faculty of Engineering in Gharyan.

$$\text{Base Case GHG emissions} = \text{Total load } \times \text{Grid electricity} - \text{specific factor } \times \text{GWP} \tag{3.41}$$

GHGs per unit emitted have a variety of effects on global warming because of gases' specific qualities. All emissions considered herein are expressed as CO_2 equivalents (CO_2e) in order to compare the emissions of various *GHGs*. This is a scale that measures the global warming potential of CO_2 in comparison with the other *GHGs* specified in the Kyoto Protocol [104]. According to the *5th* Assessment Document of the International Panel on Climate Change (IPCC) in 2014 [105], the global warming potential of methane (CH_4) and nitrous oxide (N_2O) is 21 and 310, respectively, while the value for sulfide hexafluoride (SF_6) is very high, i.e., 23,900.

The grid estimates of *GHG* emissions are determined using the following equation:

$$Grid\ GHG\ emissions = Total\ load\ supplied\ by\ the\ grid\ \times Grid_{ef} \times GWP, \tag{3.42}$$

Here $Grid_{ef}$ = Electricity-specific factor for Libya (0.919629045); $kgCO_2/kWh$ [106].

It is assumed herein that solar *PV* systems generate energy from the sun directly and produce no *GHG* emissions. Nevertheless, during their lifetime, they do emit some *GHGs*, for example when they are being built and assembled, in the balance of system, during the transfer of materials or installation, and during disposal or recycling. The emissions of the *PV* application framework, E_{mPV} are computed as follows:

$$Em_{pv} = \sum_{t=1}^{8760} P_{PV}(t) \times e_{pv} \times GWP, \quad (3.43)$$

Here:

P_{PV} = Electricity from the PV generator annually.
e_{pv} = PV framework emission factor equivalent to *47 g* CO_2*-eq/kWh* mono-Si PV emissions.

Emissions from the wind turbine system, E_{mWT}, are determined with the following equation:

$$Em_{WT} = \sum_{t=1}^{8760} P_W(t) \times e_{WT} \quad (3.44)$$

Here:

P_{WT} = Power generated by the wind turbine system annually.
e_{WT} = Emission factor of the wind turbine framework.
The overall reduction in the system's GHG emissions are calculated by

$$System_{GHG\_}total = PV_{GHG} + WT_{GHG} + Grid_{GHG} \quad (3.45)$$

$$net_{saving_{GHG}} = Base_{Case_{GHG}} - System_{GHG\_total} \quad (3.46)$$

3.11. COMPONENT ACCESSIBILITY

The reliability of a system is normally dependent on the quality of the components used, and production halts due to repairs or a complete malfunction. In addition, the probability of availability (PA) based on *PVs*, which is related to the wind turbines, is set at *96%*. Thus, the renewable energy generated from the *PVs* and the wind turbine generators can be calculated by [107–109].

$$P_{ren} = 0.966 \times (P_{pv} + P_{WT}) \tag{3.47}$$

3.12. OPTIMIZATION PROBLEM

The main aim was to establish the cheapest way to achieve the optimum number of hybrid green energy framework components. For achieving this, the *MOBA* was used in the optimization of the device's *REF* as a third objective function, while keeping the loss of likelihood of power supply and energy cost as low as possible. When seeking an optimum solution, the fact that the three functions targeted are interdependent means *LPSP* needs to be minimized, which is related to optimization of the *REF* of the system and thus increasing the *COE*, necessitating balance between the three aims during planning.

For resolving the multi-objective sizing question concerning the energy exchange between the *HRES* and the grid, the following three cases are presented.

- Case one: Sales and purchases of electricity from the grid can be conducted via the system.
- Case two: Power from the grid can only be bought via the system.
- Case three: Only sales of electricity to the grid can be conducted through the system.

Analysis of the outcomes of these cases can indicate the consequences when energy is shared between system and grid.

For applying the proposed *MOPA* and the strategy for energy management of the hybrid system, a *MATLAB* code was written to run on an Intel *Core i7-7500 2.9 GHz* processor. The simulation lasts less than an hour, and the results are used for operation over a year.

3.13. FORMULATION OF THE PROBLEM

The principal objective functions are the following:

A. First objective function: minimal energy cost

The project's *COE* is determined using Eqn. (3.48):

$$COE = \frac{(CRF \times \sum_X NPC_X) + C_{grid} - R_{grid}}{E_{served} + E_{grid\_selling}} , \tag{3.48}$$

where *CRF* is used to measure the present value while the project is running using a sequence of equivalent cash flows [105]:

$$\mathrm{CRF} = \frac{\left(\frac{\mathrm{I_r - I_f}}{1+\mathrm{I_f}}\right)\left(1+\frac{\mathrm{I_r - I_f}}{1+\mathrm{I_f}}\right)^{\mathrm{N}}}{\left(1+\frac{\mathrm{I_r - I_f}}{1+\mathrm{I_f}}\right)^{\mathrm{N}} - 1} \tag{3.49}$$

B. Second objective function: minimum loss of power supply probability:

LPSP is considered to represent the framework's reliability over a year via the equation [110] .

$$LPSP = \frac{\sum_{t=1}^{T} P_{deficit}(t) \,.\, \Delta t}{\sum_{t=1}^{T} P_{demand}(t) .\, \Delta t} ,T = 8760 \; and \;\; \Delta t = 1, \tag{3.50}$$

where $0 \leq LPSP \leq 1$.

C. Third objective function: maximum renewable energy fraction:

The *REF* is the energy component from clean sources used to supplement the load. It is determined as follows:

$$REF = \frac{\sum_{t=1}^{T}(P_{PV}+P_{WT})\times\Delta t}{\sum_{t=1}^{T}(P_{PV}+P_{WT}+P_{grid_{Purchased}})\times\Delta t}\ , T = 8760\ and\ \Delta t = 1 \qquad (3.51)$$

The grid contribution factor (GCF) represents the contribution to the electricity market. It is the opposite of the *REF* and is taken into account in order to minimize the *REF*. Reducing the GCF leads to maximization of the *REF*:

$$GCF = 1 - REF \qquad (3.52)$$

Therefore, the minimum *GCF* is included in the third objective function [111].

3.14. CONSTRAINTS

The principal functions face some restrictions:

A- Boundaries of decision variables:

$$\mathrm{N_x^{min}} \le \mathrm{N_x} \le \mathrm{N_x^{max}}\ , \mathrm{x} \in \{\mathrm{PV}, \mathrm{WT}, \mathrm{BAT}\},$$

where (Nx) represents the number of components (x).

The minimum and maximum restrictions concerning the decision variables were considered according to the problem (search space complexity and number of variables). Trial and error was used to determine these limits in all optimization algorithms.

B- Energy balance constraint:

Equivalence has to be established between the cumulative hourly energy output of all online units and the device load demand for the whole scheduled time span in order for the machine requirements is be met in terms of hourly load. That is,

$$E_{PV}(t) + E_{WT}(t) \pm E_{grid}(t) \pm E_{Bat}(t) - E_{dump}(t) \quad \geq \frac{E_{load}(t)}{\eta_{inv}} \ , \qquad (3.53)$$

Where;

E_{PV} = PV generator's energy.
E_{WT} = Wind turbine generator's energy.
E_{Bat} = Battery bank's energy generated and used.
E_{grid} = Electricity marketed, linked to storage in the system.
E_{dump} = Disposability of waste energy via overload besides grids.
ηinv = Efficiency of the inverter.

C- Battery storage parameter constraint
The battery energy capacity is limited as follows:

$$E_{Bat,min} \leq E_{Bat}(t) \leq E_{Bat,max} \qquad (3.54)$$

$E_{Bat,\ min}$ and $E_{Bat,\ max}$ are the battery banks' minimum and maximum stock sizes, respectively.

3.15. MULTI-OBJECTIVE BAT ALGORITH (MOBA)

An approach based on optimization, *MOBA*, is used herein to solve the energy management problem. The bat algorithm is bio-inspired and based on swarm intelligence. It was developed by Yang in 2010. It uses sonar echoes to detect and avoid obstacles like in bats' echolocation system. Sonic pulses are converted into frequencies reflecting obstacles [112]. The *MOBA* used herein was specifically adapted from the literature [113]. This algorithm is recommended for use in *MATLAB* with the run-time measured in seconds, depending on the purpose.

Moreover, a variety of method parameters are included, such as population size (n), reduction in loudness (α), pulse decrease rate (γ), speed (vi), and frequency (f_{min}, f_{max}) to *xi*. Clearly, the *MOBA* undergoes nearly exponential convergence. Exponential convergence in all cases is also feasible. In addition, the optimal fronts are estimated as set out in the literature [99,114].

The following strategy can be used for the actualized *MOBA*:
MOBA parameters:

BA: Population (N = 50), number of iterations = 100, loudness (α) = 0.95, pulse rate (r) = 0.45, minimum frequency (f_{min}) = 0, maximum frequency (f_{max}) = 1.

Objective functions *f*1(*x*); …; *fk*(*x*), x= (x1,..., *xd*)*T*;
Initialize the bat population *xi* (i = 1, 2, ..., n) as well as (*vi*).
for (j=1 to N) **do** (points on Pareto-fronts);
Generate *k* weights *wk* >= 0 so that:
Form a single objective.
while t < Max number of iterations **do.**
Generate new solutions by adjusting frequency.
Update velocities and locations/solutions.
if rand > ri **then;**
Random walk around a selected best solution.
end if
Generate a new solution by flying randomly;
if rand < and **then**
Accept the new solutions;
Increase and reduce.
end if.
Rank the bats and find the current x*.
end while
Record x* as non-dominated solution.
end for
Post process results and visualization.

3.16. AREA OF RESEARCH AND RENEWABLE RESOURCES

The framework proposed herein was designed for a hybrid system involving PV/wind turbines connected to a grid. In the scheme suggested for supplying the Faculty of Engineering with power, the electricity generated by the PV system linked to the wind turbines is used. Surplus energy is used to charge the batteries and is only directed to the grid when the batteries are fully charged. In addition, the batteries' power is used first if the energy services of the Faculty of Engineering are not accessible from the PV network connected to the wind turbines. If the generators do not meet the demand, energy is supplied by the grid.

The study was performed at 32°10.6′N and 13°1.6′E, at the Faculty of Engineering in Gharyan, Libya. The area is characterized by RES with a mean radiation of 2047 kWh/m^2 per year and mean wind speeds of 5.31 m/s. The Faculty's electricity use is as follows: mean 112.8 kWh per hour, total output 199 kW, and charging factor 0.636. The usual regular load for a year (March, July, and December) is shown in Figure 3.8.

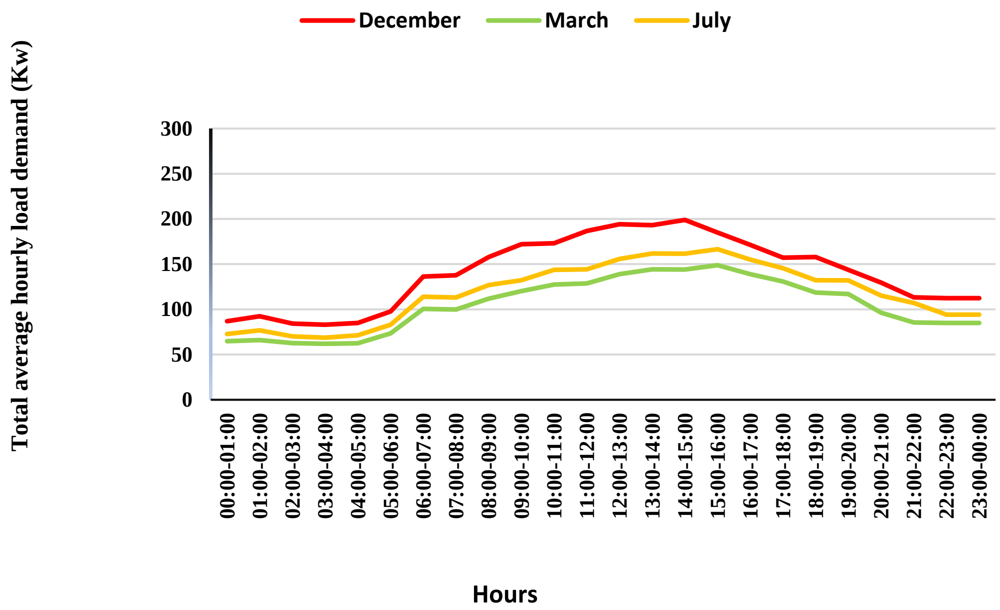


Figure 3.8. The study area's daily average load profile for the months of March, July, and December.

Concerning the products commercially available in Libyan, various components were chosen from among those available, and their prices were learned from different companies supplying manufacturers. The appropriate components were thus selected with regards to operating and repair costs, and life and essential costs as well as any further expenses. Table 3.3 shows the components selected along with their prices.

Table 3.3. Features of the components selected and their costs.

Component	Cost of Capital ($)	Cost of Replacement ($)	Operating and Maintenance Costs ($)	Duration of Life (Years)
PV (15 kW)	21000	0	(1) Percentage for cost of PV panel [115]	20
Wind Turbine (10 kW)	11000	0	(3) Percentage for cost of wind turbine [115]	20
375-Ah Nickel-Iron Battery	15200	15200 × Rate of price increase		20
Charge Controller	1200			15

CHAPTER 4

EXPERIMENTAL RESULTS

4.1. SIMULATION RESULTS

The dynamic and static economic and emission dispatches were validated using *SPVPPs*. The case study system used for testing comprises *10 IEEE* thermal units and *13 SPVPPs*. The data concerning these thermal units and their emissions are shown in Table 4.1.

Table 4.1. Data on the generation and emissions of ten thermal power plant units.

Unit No	**A**	**b**	**c**	**Pmin**	**Pmax**	**α**	**β**	**γ**	**e**	**f**
1	0.128	40.432	1011.393	11.000	56.000	0.043	-3.899	359.003	0.261	0.014
2	0.112	40.780	962.599	21.000	81.000	0.043	-3.987	349.011	0.261	0.014
3	0.131	36.499	907.803	48.000	119.000	0.043	-3.914	329.011	0.265	0.014
4	0.128	40.010	808.698	21.000	129.000	0.043	-3.914	329.011	0.265	0.014
5	0.149	38.487	761.802	51.000	159.000	0.0039	0.331	14.065	0.261	0.014
6	0.111	46.161	465.345	71.000	239.000	0.0039	0.331	14.065	0.261	0.014
7	0.041	38.298	1252.631	61.000	299.000	0.0068	-0.551	39.176	0.254	0.015
8	0.031	40.403	1054.765	71.000	339.000	0.0068	-0.551	39.176	0.261	0.014
9	0.019	36.299	1662.603	129.000	469.000	0.0049	-0.509	41.876	0.261	0.014
10	0.021	39.306	1365.712	149.000	469.000	0.0049	-0.509	40.966	0.268	0.014

The area of research at the beginning is the center for solar energy and it is at the Engineering Faculty in Gharyan, Libya, at *32°10.6'N and 13°1.6'E*.

The *SPVPP* data are shown in Table 4.2 while the hourly solar irradiation, temperature, and energy demand are given in Table 4.3.

Table 4.2. Ratings and the cost per units of generation in *SPVPPs*.

Plant	Prated (kW)	Unit rate ($/kWh)
1	20	0.22
2	25	0.23
3	25	0.23
4	30	0.24
5	30	0.24
6	35	0.25
7	35	0.26
8	40	0.27
9	40	0.27
10	40	0.275
11	40	0.28
12	40	0.28
13	40	0.28

Table 4.3. Solar irradiation, temperature, and energy demands of the system on an hourly basis.

Time (h)	Solar Irradiation (W/m^2)	Energy Demands (MW)	Temperature (°C)
1	0	965	30
2	0	1142	29
3	0	1177	28
4	0	1198	28
5	5.4	1153	28
6	101	1136	28
7	253.7	1138	29
8	541.2	1060	31
9	530.4	1155	33
10	793.9	1244	34
11	1078	1088	35
12	1125.6	1240	36
13	1013.5	1135	37
14	848.2	1318	37
15	726.7	1074	37
16	654	1190	38
17	392.9	1276	38
18	215.1	1154	37
19	38.5	1333	35
20	0	1322	34
21	0	1269	34
22	0	1139	33
23	0	1202	32
0	0	1291	32

MATLAB was used to test the hybrid bat-crow search algorithm for cost and emissions combined via *SPVPPs*. Convergence graphs hours are divided into three parts and shown in Figures 4.1, 4.2, and 4.3 for 24 hours.

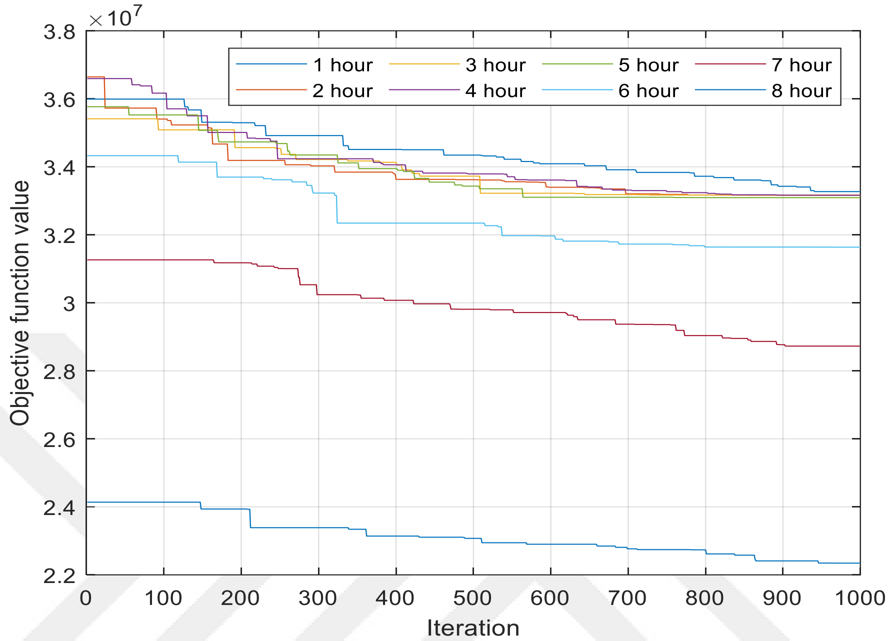


Figure 4.1. Convergence curve for *1* to *8* hours.

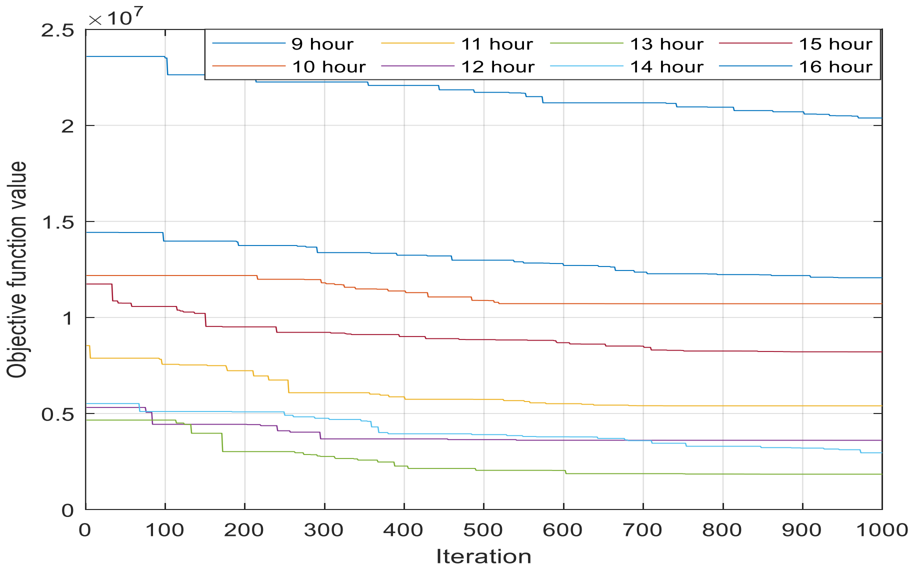


Figure 4.2. Convergence curve for *9* to *16* hours.

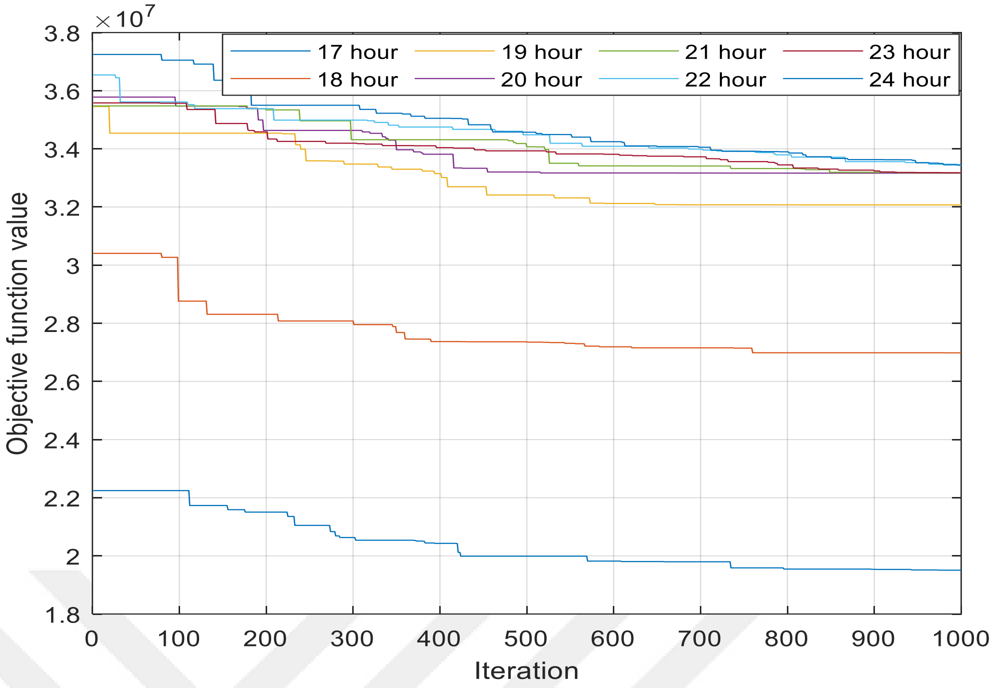


Figure 4.3. Convergence curve for *17* hours to *24* hours.

As shown in Figure 4.1, convergence of the algorithm occurs within *900* iterations in a maximum of *2.16* s when using a *4-GHz Core i7* processor. After *900 iterations* the value of the objective function for *8* hours is 2.3×10^7. For other hours the value is above 2.9×10^7.

As shown in Figure 4.2, convergence occurs within *440* iterations. After *440* iterations the value of the objective function for *12* hours is 0.045×10^7. This is 1.98×10^7 for *9* hours and is above 2.9×10^7 for other hours. In the last *8* hours (Figure 4.3), convergence occurs within *620* iterations. After *620* iterations the value of the objective function for *17* hours is 1.9×10^7. For other hours it is above 2.61×10^7.

Thermal power, solar power emission costs, power loss, solar power costs, fuel expenses, and combined economic and emission costs with solar costs are summarized in Table 4.4.

Table 4.4. CEED analysis and solar cost.

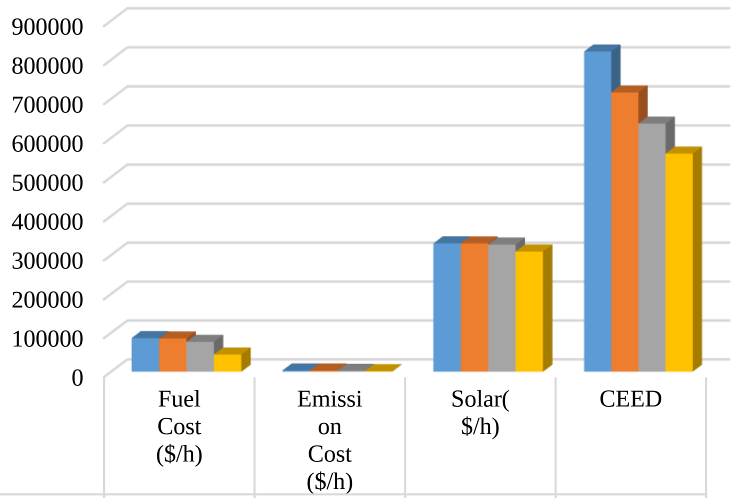
Time	Demand	Pot	SP	Pl	FC	EC	TC
Hour	MW	MW	MW	MW	$/kWh		
1	974	967.085	0	11.918	42197.9	1468.09	43653.05
2	1176	1165. 95	1	14.408	45304.3	1416.71	46815.1
3	1189	1178.84	0	15.152	46475.42	1467.9	47931.33
4	1210	1193.91	5	16.0694	47463.36	1516.4	48967.7
5	1167	1170.43	0	14.5675	45845.1	1464.7	47293.8
6	1176	1146.07	19.76	14.189	45567.41	1423.45	47301.5
7	1176	1095.37	53.236	14.398	45196.82	1423.09	47611.4
8	1080	943.399	137.974	12.668	42834.34	1448.4	46891.1
9	1176	996.576	156.694	14.799	45692.32	1483.6	50201.6
10	1274	994.741	248.52	16.737	48773.05	1502.5	55153. 2
11	1108	770.612	356.4	12.981	44062.63	1496.82	52072.45
12	1278	873.384	382	15.615	48834.66	1475.7	57742.3
13	1176	792.049	349.5	16.453	45221.91	1487.3	53501.3
14	1348	918.802	395.4	18.784	51102.36	1546.3	60542.7
15	1094	770.708	329.7	13. 925	43595.67	1465.17	51492.21
16	1230	829.635	368	15.362	47065.72	1445.3	55632.94
17	1293	887.29	392.8	16.911	49734.32	1523.8	58892.00
18	1186	797.23	367.2	14.697	45935.86	1484.5	54333.5
19	1373	975.762	403.7	19.38	51693.34	1545.3	61223.6
20	1392	1334.93	1	18.012	51334.54	1562.1	52886.2
21	1297	1273.73	1	16.25	49786.65	1527.2	51301.3
22	1186	1156.64	1	14.338	45476.45	1441.7	46921.21
23	1231	1197.93	0	15.0065	50387.57	1734.8	52101.3
24	1302	1295.19	0	16.807	50576.93	1512.7	52078.76

The solar plant was studied when both *ON* and *OFF* for various hours, and the results are given in Table 4.5.

Table 4.5. *SPVPPs* when *ON* and *OFF* in different hours.

Solar Plant												
1	2	3	4	5	6	7	8	9	10	11	12	13
0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0
0	1	0	1	0	1	1	1	1	1	1	0	1
0	0	0	1	1	1	1	1	1	1	1	1	1
1	1	1	0	1	1	1	1	0	1	1	1	1
1	0	1	1	0	1	1	1	1	1	1	1	1
1	1	1	0	1	1	1	1	1	1	1	1	1
1	1	1	1	1	0	1	0	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1	1
1	0	0	1	1	1	0	1	1	1	1	1	1
0	1	1	1	0	1	1	1	1	0	1	1	1
0	1	1	1	1	1	1	1	1	1	1	1	1
1	0	1	0	1	1	1	1	1	1	1	1	1
1	0	1	1	1	1	0	1	1	1	1	1	1
1	0	1	1	1	1	1	1	1	1	1	1	1
1	1	0	1	1	1	1	1	1	1	1	1	1
0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0

These findings clearly show that the use of solar *PV* energy led to major decreases in emissions and fuel costs in the system. This hybrid algorithm manages the percentages of energy supplied by thermal power plants and *SPVPPs* successfully. Thus, the algorithm is the most successful in terms of optimizing the combination of emission and economic dispatches with *SPVPPs*. The findings for the *PSO*, bat, and crow search algorithms are compared and the usefulness of the method proposed in terms of fuel cost, emission cost, solar cost, and *CEED* is shown in Figure 4.4.



	Fuel Cost ($/h)	Emission Cost ($/h)	Solar($/h)	CEED
PSO	86503	3281	329899	821098
Bat Algorithm	85548	3081	329786	716198
Crow Search Algorithm	76748	2290	326897	636402
Proposed Bat- Crow Algorithm	44198	1442,1	309105	559698

Figure 4.4. Results for the bat algorithm, crow search algorithm and proposed method in terms of fuel cost, emission cost, solar cost, and *CEED*.

In Figure 4.4 it is seen that the method proposed results in the lowest cost among all the methods considered here. This proves that it performs better than when the three algorithms are used separately; in other words, the bat and crow algorithms yield good results when combined.

Finally, we compared the process time for each algorithm that used in this simulation. The result is shown in figure 4.5.

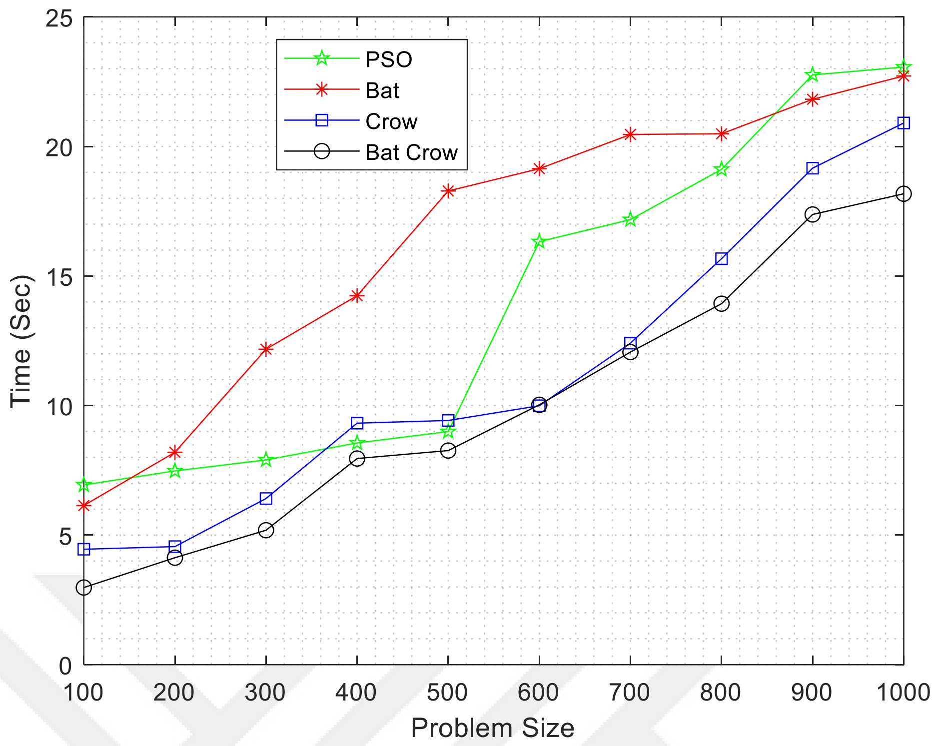


Figure 4.5. The convergence speed of different algorithms.

Figure 4.5, it can be inferred that using the proposed Bat-Crow algorithm to the selection and migration operators enhances the algorithm's convergence speed considerably when compared to other techniques. This is because using these maps improves the algorithm's exploration power and expands the search space. This improved search space exploration improves convergence speed and prevents the algorithm from becoming stuck in local minimums. Also as seen in this figure the proposed Bat-Crow search algorithm has low process time than other methods.

The hybrid method produces better results because the crow algorithm has a specific initial population that is useful for solving the bat algorithm. It is proposed herein to use the hybrid algorithm for minimizing the cost from combined *ED* between *10* conventional and *13* solar *PV* power plants. The cost comprises fuel cost, emission cost, solar cost, and the state of sharing cost. Lower cost is obtained from the hybrid algorithm than from the *PSO*, bat, and crow algorithms.

The *ED* problem in thermal power and solar *PV* generators is described here. In general, these problems may be formulated using a static or dynamic model. Both case studies were performed, and the corresponding numerical model is shown below.

This is illustrated for the two-dimensional case in Figure 4.6.

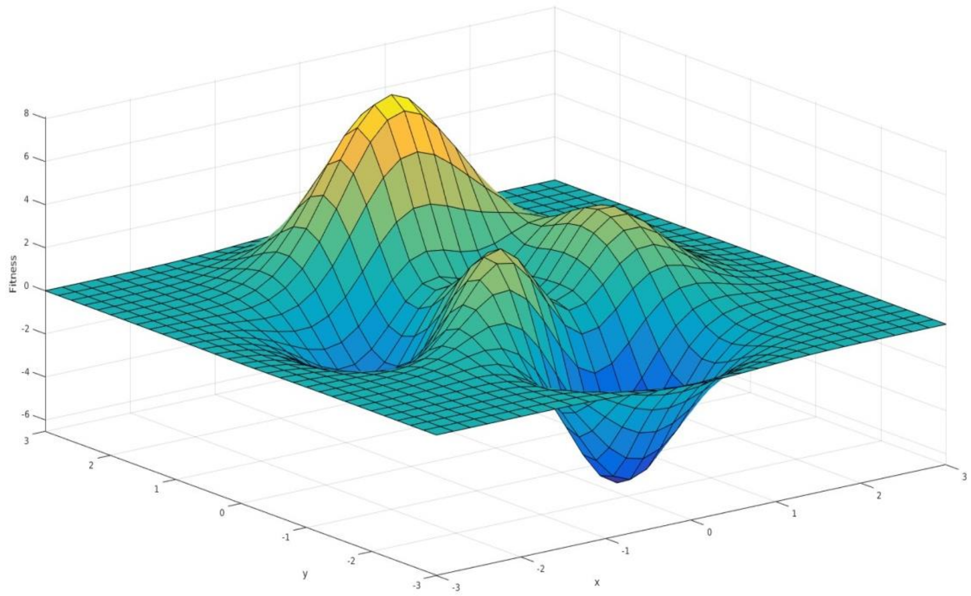


Figure 4.6. A discretized *2-D* fitness function.

The *PSO* search algorithm for combined economic and emission dispatch with *SPVPP* was tested using *MATLAB* in an *Intel Core i7* processor. Convergence graphs for *24* hours are shown in *3* parts in Figures 4.7, 4.8, and 4.9.

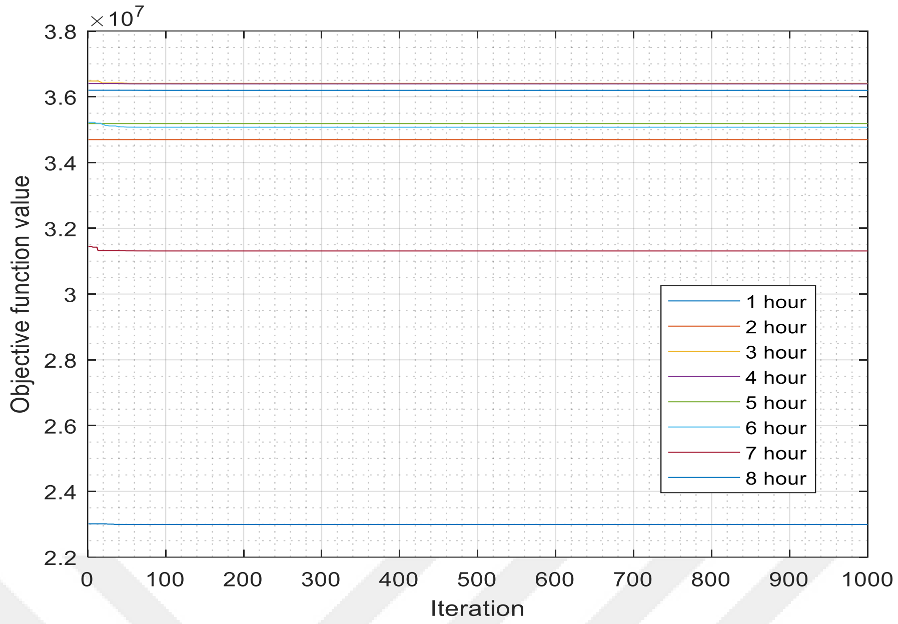


Figure 4.7. Convergence curve for *1* hour to *8* hours.

This figure shows that convergence occurs within *30* iterations, which is equivalent to a maximum of *2.16* s with a *4 GHz* core *i7* processor. After *1000* iterations the value of the objective function for *8* hours is 2.3×10^7. For other hours it is above 2.9×10^7.

Elapsed time for *1* to *8* hours is shown in Figure 4.10.

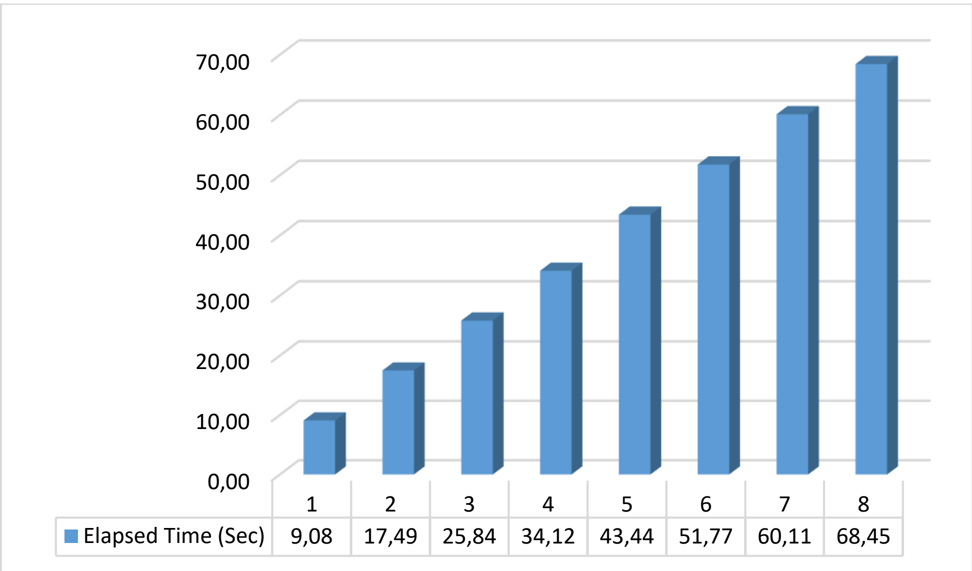


Figure 4.8. Elapsed time for *1* to *8* hours.

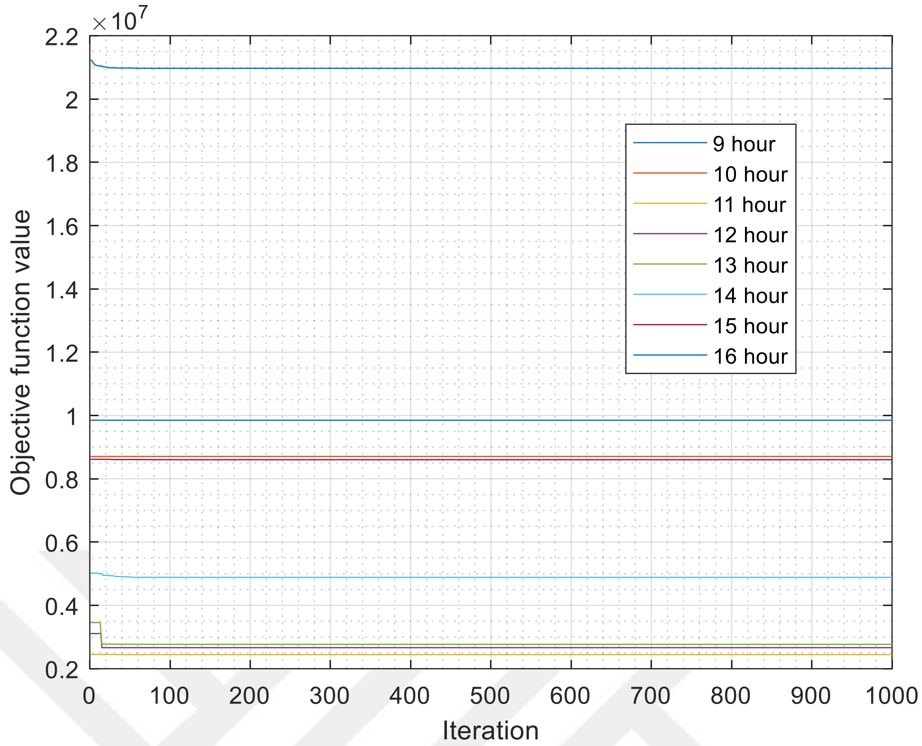


Figure 4.9. Convergence curve for *9* hours to *16* hours.

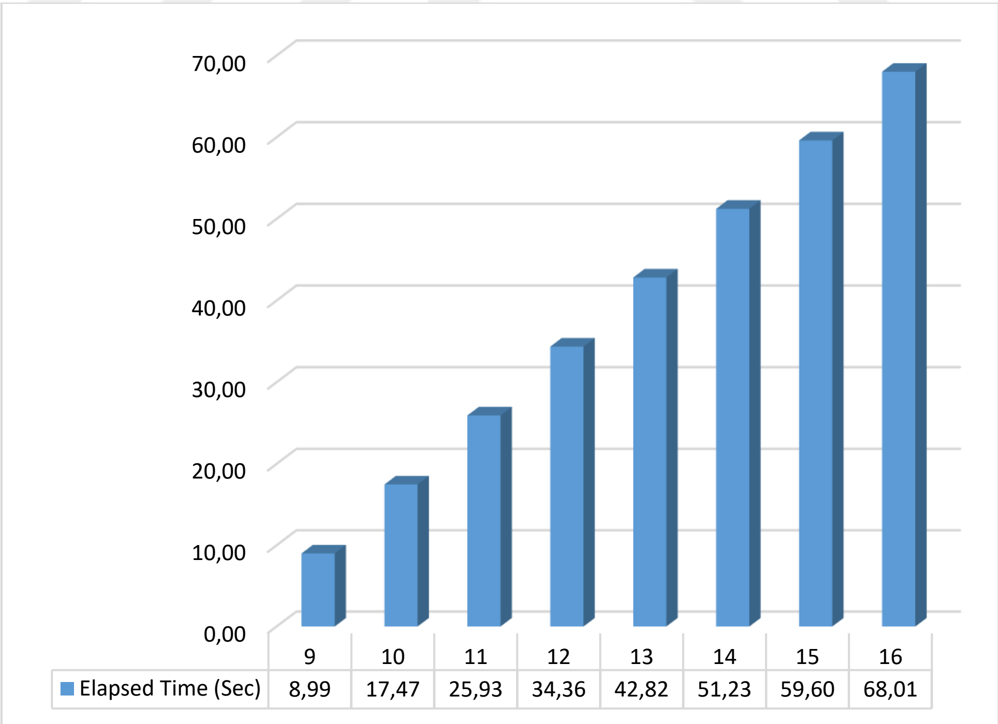


Figure 4.10. Elapsed time for *9* to *16* hours.

As seen in this figure, convergence occurs within 30 iterations. After *30* iterations the value of the objective function for *15* hours is 0.25×10^7. For *9* hours it is 1.98×10^7 and for other hours it is above 2.9×10^7. The convergence curve for *17* hours to *24* hours is shown in Figure 4.11.

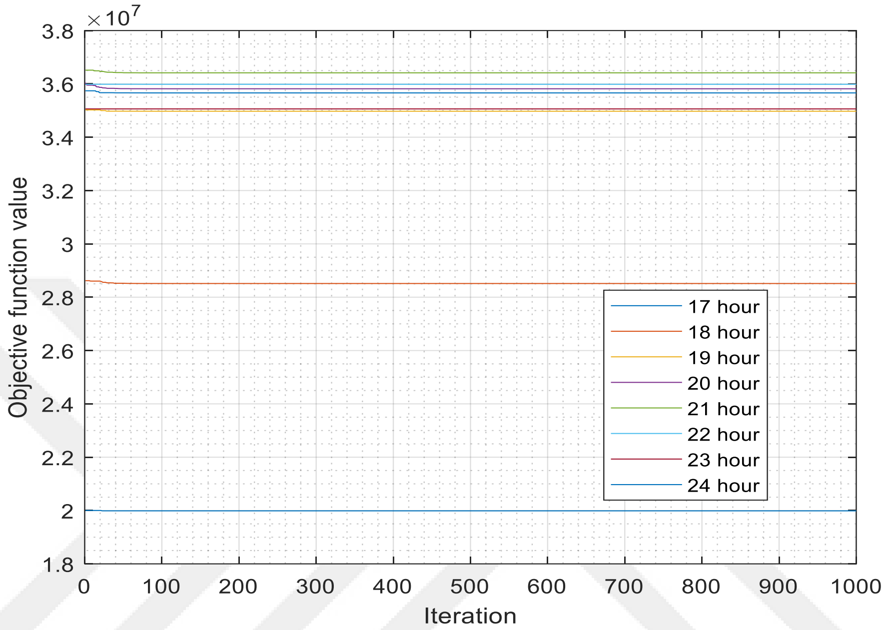
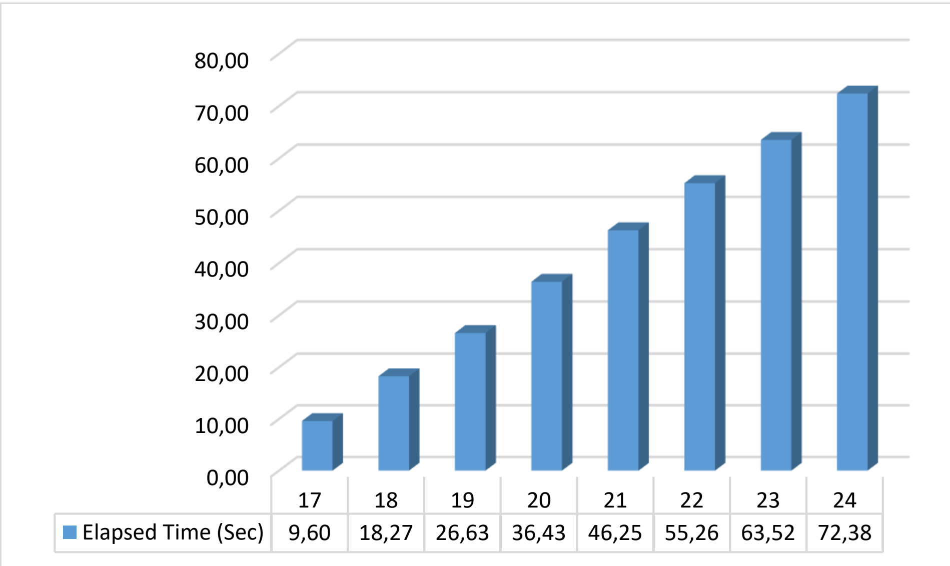


Figure 4.11. Convergence curve for *17* hours to *24* hours.

Elapsed time for *17* to *24* hours is shown in Figure 4.12.



	17	18	19	20	21	22	23	24
Elapsed Time (Sec)	9,60	18,27	26,63	36,43	46,25	55,26	63,52	72,38

Figure 4.12. Elapsed time for *17* to *24* hours.

Table 4.6 shows the results for thermal power, solar power, power loss, fuel cost, solar power cost, emission cost, and combined economic and emission cost with solar cost.

Table 4.6. *CEED* analysis with solar cost via the *PSO* method.

Time	Demand	Pot	SP	Pl	FC	Irradiation	EC	TC
Hour	MW	(MW)	(MW)	(MW)	($/kWh)	/	/	/
1	963	1124.583	440000	23.38848	61773.48	0	1856.581	598371.4
2	1142	1074.961	440000	22.47567	58267.36	0	1784.818	591131.4
3	1177	1086.853	440000	22.12171	60925.81	0	1852.54	597313.5
4	1198	886.7549	440000	14.68616	49273.21	0	1565.37	570719.4
5	1153	965.4468	439049.8	17.58578	54510.44	0	1800.766	587254.1
6	1136	1004.019	422228.6	17.87347	54821.99	355.52	1681.048	564515.5
7	1138	1116.576	389780.5	21.02342	59909.43	1004.652	1835.567	545194.4
8	1060	1106.704	309063.6	17.88002	54136.79	2619.408	1815.81	457677
9	1155	1257.824	288345	22.39013	61250.26	3033.888	1820.225	444301.6
10	1244	1342.966	195542.3	22.28864	60612.01	4890.424	1771.636	348332.6
11	1088	1445.299	112642.9	23.34002	61191.84	6528	1789.004	266916.6
12	1240	1449.652	115910.2	23.81131	61789.95	7440	1934.362	278345
13	1135	1281.085	112725.6	16.65843	54325.88	6810	1635.695	252156.7
14	1318	1319.243	122855.6	18.68421	54815.45	7908	1762.357	269366.5
15	1074	1340.347	168284.8	20.6472	59915.57	6444	1893.828	326736.3
16	1190	1316.345	181083.3	20.73662	59399.7	7140	1763.929	332260.2
17	1276	1276.249	284452	23.82309	60406.58	7656	1867.86	442043.4
18	1154	1102.829	359573.5	19.14874	57846.93	6924	1679.831	504822.1
19	1333	1056.921	427298.3	21.16889	56358.15	7998	1762.58	575363.5
20	1322	1079.451	440000	20.93744	60402.25	0	1815.111	594842.5
21	1269	978.9142	440000	17.39472	55548.44	0	1641.294	580945
22	1139	930.5013	440000	16.08157	52920.19	0	1632.683	577868.7
23	1202	1043.826	440000	20.20332	58158.47	0	1736.955	588532.2
24	1291	949.829	440000	16.85681	52544.07	0	1588.3	575183.3

The proposed method was used to analyze a hybrid *PV* and wind network connected to a grid meeting the need of the Faculty of Engineering in Gharyan, Libya. Thus, the multi-objective issue concerning the sharing of electricity between the *HRES* and the grid was examined for the three situations listed below:

- Case one: The purchasing and selling of electricity from the grid with be conducted via the system.

- Case two: Only the buying of energy from the grid can be done via the system.
- Case three: The system can only be used to sell energy to the grid.

A one-hour *MATLAB* code was used in the simulation, with data over a year with 8784samples/year, and a discounted cash flow (DCF) was applied over 20 years in order to calculated the system's total net present cost (TNPC).

The results are divided into *3* categories. Table 4.7 contains the results obtained from the *MOBA* review of the sizing problem:

- The lowest economically optimal *COE* solution.
- Use of renewable energy with the highest *REF*.
- Optimal solution giving the lowest emissions of *GHGs*.

Table 4.7 shows convergence of the results for the first and second cases in terms of the goals, but they are considerably surpassed by the results for the third case. Economically speaking, the *COE* value for the first and second cases converges at *0.0313 $/kWh* and *0.0317 $/kWh*, respectively, at zero *LPSP*. However, for the third case, *COE* is much higher, *$0.365/kWh*, when the system is dependent on renewable energy supplies alone and excess energy is not exported to the grid. It is worth noting that the sale price of electricity in Libya is *$0.04/kWh*, which is above the price in the first and second cases.

From the perspective of renewable energy consumption, in the first and second cases, the sale price of the energy unit rose by *127.68 percent* in economic terms, and the share of *LPSP* grew to *1.39 percent* and *2.05 percent*, respectively. In the third case, however, the criterion is reliability (minimum LPSP) rather than renewable energy use, since *REF* is constant at *100 percent*.

Table 4.7. Results for the size problem in the three cases.

Cases	Objective	COE ($/kWh)	NPC	LPSP (%)	REF (%)
Case one	Economic	0.0313	361716.6	0.00%	40%
	Renewable energy usage	0.0876	1009117.8	1.39%	78%
	Environment	0.0874	1009117.7	1.39%	78%
Case two	Economic	0.0317	364709	0%	41%
	Renewable energy usage	0.0914	1042977.4	2.05%	78%
	Environment	0.0914	1042977.4	2.05%	78%
Case three	Economic	0.365	4019002	5.23%	100%
	Reliability (lowest LPSP)	0.457	5307404	0.115%	100%
	Environment	0.365	4019002	5.21%	100%
Cases	Objective	N_{PV}	N_{WT}	N_{BAT}	Total emissions of GHGs per ton
Case one	Economic	30	0	0	109939.4
	Renewable energy usage	39	11	2	85714
	Environment	39	11	2	85714
Case two	Economic	32	0	0	109939.4
	Renewable energy usage	36	11	5	85128
	Environment	36	11	5	85128
Case three	Economic	132	14	172	27231.6
	Reliability (lowest LPSP)	152	36	224.7	32061.6
	Environment	132	14	172	27231.6

When a machine running at a low *LPSP* of *0.115 percent* was used, *COE* rose by *127.68 percent*. In environmental terms, it is clear that the third case produces the highest *GHG* emissions, with an annual mean of *27231.6 tons*, compared with *85714* and *85128 tons* for the *first* and *second* cases, respectively. The large increase in the cost of the system, regarding both renewable energy use and the environment, can be explained by the fact that the objective is greater dependency on *RES* instead of obtaining energy from the grid, which is plainly less expensive. The steep cost of the system overall is a result of the high dependency on wind turbines and *PV* systems.

The amount of energy produced in the three cases in shown in Table 4.8 for each variable. In the *first* case, with regard to the use of renewable energy and the environmental perspective, the electricity produced by wind turbines that were not used when the economic perspective was considered makes up for the fact that power is not bought from the grid.

The total power generated by the *PV* system and the wind turbines rose from *509.15 MWh* to *636.44 MWh* and from zero to *300.947 MWh*, respectively, and the total power purchased from the grid fell from *761.184 MWh* to *565.342 MWh*. In the *second* case, since power is not bought from the grid, there was an idle surplus of *63.45 MW* in terms of the economic perspective, and this increased to *298 MW* regarding the use of renewable resources and the environmental perspective.

In the *third* case, in which it is not allowed to obtain power from the grid, there was greater dependence on the *PV* system for power production. The amount produced by the *PV* system was *2202.13 MW* at *93.3 percent* with regard to both economic and environmental perspectives and rose to *2545.81 MW* at *88.67 percent* with regard to reliability. While the power generated by the wind turbines was *108.34 MW* (*6.8 percent*) with regard to both economic and environmental perceptions, it increased sharply to *294.92 MW* (*10.33 percent*) with regard to reliability.

For establishing how the Pareto fronts (PFs) are related to the three objectives (COE, LPSP, and REF), the *COE PF* and *LPSP PF* are shown together in Figure 4.12, and the *COE PF* and *REF PF* are shown together in Figure 4.14. In the *first* and *third* cases, *LPSP* has a minimal effect on *COE*, where most of the outcomes are concentrated near *0* in terms of *LPSP*. However, in the third case, the system might be regarded as an off-grid system. Please refer to Figure 4.14. Furthermore, the *COE* rises due to the rise in *REF*, and more *PV* units and wind turbines are used in the hybrid framework, which makes the framework’s energy unit more expensive.

Table 4.8. The electricity produced in the *three* cases for each component.

Cases	Objective	P_{PV} (MWh)	P_{WT} (MWh)	Sell to grid (kWh)	Purchase from grid (MWh)
Case One	Economic	510.21	-	63.815	763.23
	Renewable energy usage	638.53	302.67	280.76	567.41
	Environment	638.53	302.67	280.76	567.41
Case Two	Economic	510.21	-	-	761.184
	Renewable energy usage	638.53	302.67	-	563
	Environment	638.53	302.67	-	563
Case Three	Economic	2214.26	112.42	954.56	-
	Reliability (lowest LPSP)	2565.46	298.8	1453.51	-
	Environment	2214.26	112.42	954.56	-
Cases	Objective	Proportion of PV (%)	Proportion of wind turbines (%)	Propo53rtion of grid (%)	Emissions net savings in CO_2 (%)
	Economic	41	0	59%	24.2%
Case One	Renewable energy usage	42	20	35	41.8%
	Environment	42	20	35	41.8%
	Economic	40	0	58%	24.2%
Case Two	Renewable energy usage	41.8	18	37.6	41.8%
	Environment	41.8	18	37.6	41.8%
	Economic	92.6%	5.8%	0	81.4%
Case Three	Reliability (lowest LPSP)	87.72%	11.33 %	0	76.65%
	Environment	92.6%	5.8%	0	81.4%
Case Two	Economic	62.93			
	Renewable energy usage	276.1	Dump of Energy (MWh)		
	Environment	276.1			

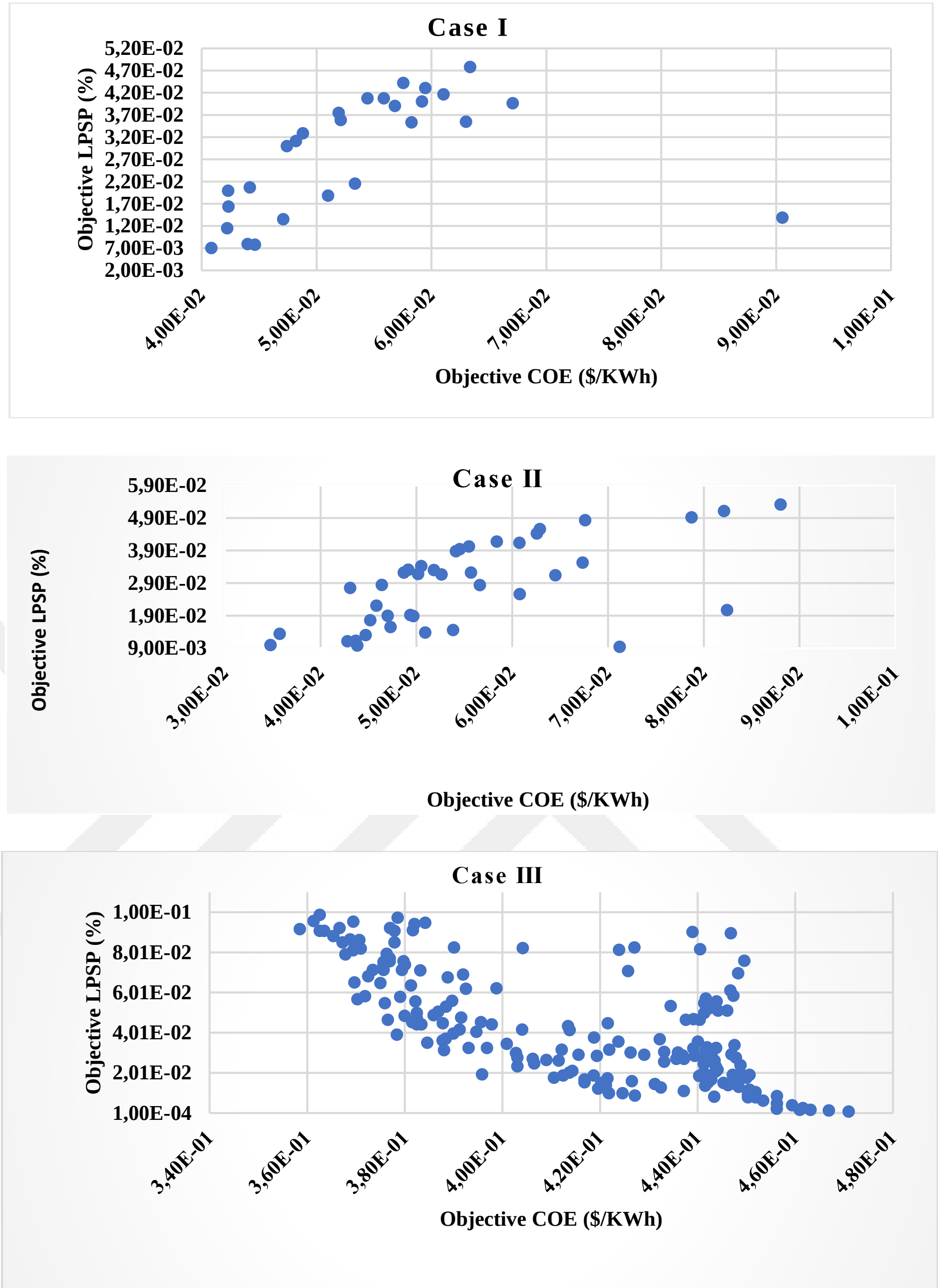


Figure 4.13. Pareto fronts of *COE* and *LPSP* in the three cases.

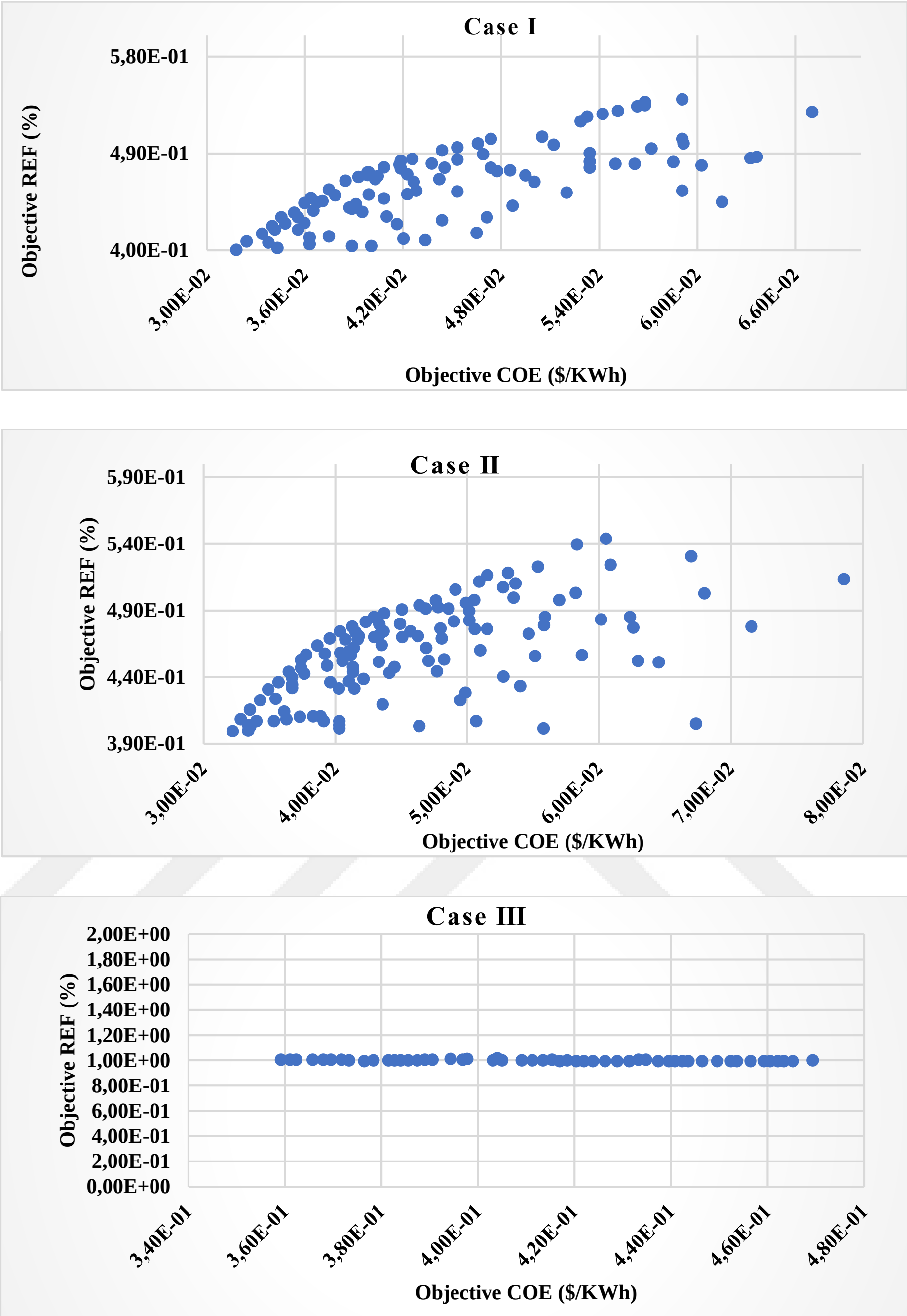


Figure 4.14. Pareto fronts of *COE* and *REF* in the three cases.

4.2. PERFORMANCE EVALUATION

The proposed *MOBA* is assessed differently in terms of performance from the single-objective *BA* since for the former different options are available. To determine the *MOBA's* performance, various statistical metrics were used, namely minimum, maximum, mean, standard deviation, and average Pareto solutions. The results of the evaluation are summarized in Table 4.9.

Table 4.9. Performance metrics determined with the *MOBA* for Pareto solutions in the *three* cases.

Case	Objectives	Min.	Max.	Mean
Case one	Obj. 1 (COE)	0.032	0.091	0.063
	Obj. 2 (LPSP)	00	0.039	0.030
	Obj. 3 (REF)	0.36	0.91	0.603
Case two	Obj. 1 (COE)	0.0321	0.094	0.0620
	Obj. 2 (LPSP)	000	0.062	0.0316
	Obj. 3 (REF)	0.36	0.82	0.602
Case three	Obj. 1 (COE)	0.372	0.496	0.439
	Obj. 2 (LPSP)	0.0023	0.0909	0.0504
	Obj. 3 (REF)	1	1	1

CHAPTER 5

CONCLUSION AND FUTURE RESEARCH

5.1. CONCLUSION

Based on the principles of sensor use for determining fatigue failure in steel bridges, the stages that should be considered are detailed below.

Various numerical and optimization techniques are used for determining optimal power system costs, raising system efficiency, and solving *CEED* problems. Better results and designs may be achieved by heuristic methods as mathematical data and gradient information are not needed. In the present thesis, a hybrid method is suggested for finding a solution to this optimization problem more quickly and more accurately. A novel hybrid bat-crow search algorithm for minimizing *CEED* problems via a solar *PV* system in a multi-area system was described. The efficiency of this algorithm was tested over *24* hours with the data from a solar system and *10* thermal power plants. In addition, the algorithm was used to calculate the economic costs, convergence efficiency, and *SPVPPs* in both *ON* and *OFF* conditions. The hybrid algorithm was successful in minimizing complex problems in a multi-area power system. Furthermore, a comparison of four parameters was conducted. The fuel cost, emission, solar cost, and *CEED* were determined as *44203 $/h, 1449.6 $/h, 439.870 $/h, and 558900*, respectively. These results were compared with those obtained using other techniques, i.e., *PSO*, the bat algorithm, and the crow search algorithm. The hybrid algorithm produced lower results for fuel cost, emission cost, solar cost, and *CEED* compared with those of the other techniques.

We aimed herein to produce a grid-connected renewable energy framework to supply ongoing stable energy in the least expensive way under varying conditions. The objective was to meet the demand of the Faculty of Engineering in Gharyan, Libya, via a *PV*/wind hybrid grid-connected system. The optimization problem involved *3* major objective functions: minimizing *COE*, decreasing *LPSP*, and optimizing the *REF* of the proposed method. Furthermore, to enable an optimal variety of elements the *MOBA* was used.

For solving the multifunctional energy exchange problem between the *HRES* and the grid *three* cases were examined. In the *first* case, sales and purchases of energy from the grid are permitted; in the *second* case, only sales of energy from the grid are permitted; and *finally*, in the *third* case, only sales of energy to the grid are permitted.

In summary, the results obtained from this *MOBA* research on the sizing issue were examined in three cases with focus on the economic, renewable energy, and environmental perspectives. The framework simulation results led to the following conclusions:

- An elevated *REF* ratio is linked to high *COE* and *LPSP* values. Moreover, a higher *REF* gives a greater total value of both the *PV* and wind turbine systems, with a subsequent increase in the *COE*.
- In the *third case*, there is a steep rise in overall cost, since the energy demand is now met by the renewable framework, i.e., off-grid.

The *first case* is financially optimal since the total current framework cost was *$361716.6*, with costs for the *second and third* cases being *$364709* and *$4019002*, respectively.

5.2. FUTURE WORK

In the future we can apply the proposed algorithm to different meta-heuristic methods, and we can use the artificial intelligence and deep learning method for training the data and use them in the real world. Also we can use fuzzy logic based on the neural network and obtain the tunable value for the controlling parameter in the method proposed.

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APPENDIX A.

MATLAB CODES

```
%CSA for CEED Optimization
close all; clear all; clc
tic
global data B Pd data1 Bi0 B00 PL_solar PL_D Solar_data Ks Solar_env Pgs hour
lam1

%Plant data
%no of rows denote the no of plants(n)
 da-
ta=[0.129510000000000,40.5407000000000,1000.40300000000,10,55,33,0.0174000
000000000;

0.109080000000000,39.5804000000000,950.606000000000,20,80,25,0.0178000000
000000;

0.125110000000000,36.5104000000000,900.705000000000,47,120,32,0.016200000
0000000;

0.121110000000000,39.5104000000000,800.705000000000,20,130,30,0.016800000
0000000;

0.152470000000000,38.5390000000000,756.799000000000,50,160,30,0.014800000
0000000;

0.105870000000000,46.1592000000000,451.325000000000,70,240,20,0.016300000
0000000;

0.0354600000000000,38.3055000000000,1243.53100000000,60,300,20,0.01520000
00000000;

0.0280300000000000,40.3965000000000,1049.99800000000,70,340,30,0.01280000
00000000;

0.0211100000000000,36.3278000000000,1658.56900000000,135,470,60,0.0136000
000000000;

0.0179900000000000,38.2704000000000,1356.65900000000,150,470,40,0.0141000
000000000];
% Loss coefficients it should be squarematrix of size nXn where n is the no
% of plants
B=[0.000049 0.000014 0.000015 0.000015 0.000016 0.000017 0.000017 0.000018
0.000019 0.000020
   0.000014 0.000045 0.000016 0.000016 0.000017 0.000015 0.000015 0.000016
0.000018 0.000018
   0.000015 0.000016 0.000039 0.000010 0.000012 0.000012 0.000014 0.000014
0.000016 0.000016
   0.000015 0.000016 0.000010 0.000040 0.000014 0.000010 0.000011 0.000012
0.000014 0.000015
```

```
   0.000016 0.000017 0.000012 0.000014 0.000035 0.000011 0.000013 0.000013
0.000015 0.000016
   0.000017 0.000015 0.000012 0.000010 0.000011 0.000036 0.000012 0.000012
0.000014 0.000015
   0.000017 0.000015 0.000014 0.000011 0.000013 0.000012 0.000038 0.000016
0.000016 0.000018
   0.000018 0.000016 0.000014 0.000012 0.000013 0.000012 0.000016 0.000040
0.000015 0.000016
   0.000019 0.000018 0.000016 0.000014 0.000015 0.000014 0.000016 0.000015
0.000042 0.000019
   0.000020 0.000018 0.000016 0.000015 0.000016 0.000015 0.000018 0.000016
0.000019 0.000044];
Bi0 = 0.001 *[ 0.287 0.012 0.0896 0.1471 0.0087 0.3121 0.233 0.1123 0.0912
0.1121];
B00 = 0.038;

%Emission data
  data1=[0.0470200000000000,-
3.98640000000000,360.001200000000,10,55,0.254750000000000,0.0123400000000
000;
         0.0465200000000000,-
3.95240000000000,350.005600000000,20,80,0.254750000000000,0.0123400000000
000;
         0.0465200000000000,-
3.90230000000000,330.005600000000,47,120,0.251630000000000,0.012150000000
0000;
         0.0465200000000000,-
3.90230000000000,330.005600000000,20,130,0.251630000000000,0.012150000000
0000;

0.00420000000000000,0.327700000000000,13.8593000000000,50,160,0.249700000
000000,0.0120000000000000;

0.00420000000000000,0.327700000000000,13.8593000000000,70,240,0.249700000
000000,0.0120000000000000;
         0.00680000000000000,-
0.545500000000000,40.2669000000000,60,300,0.248000000000000,0.01290000000
00000;
         0.00680000000000000,-
0.545500000000000,40.2669000000000,70,340,0.249900000000000,0.01203000000
00000;
         0.00460000000000000,-
0.511200000000000,42.8955000000000,135,470,0.254700000000000,0.0123400000
000000;
         0.00460000000000000,-
0.511200000000000,42.8955000000000,150,470,0.254700000000000,0.0123400000
000000];

Solar_data=     [1 20 0.22
```

```
              2 25 0.23
              3 25 0.23
              4 30 0.24
              5 30 0.24
              6 35 0.25
              7 35 0.26
              8 40 0.27
              9 40 0.27
              10 40 0.275
              11 40 0.28
              12 40 0.28
              13 40 0.28];
Solar_env=  [1 0 965 30
           2 0 1142 29
           3 0 1177 28
           4 0 1198 28
           5 5.4 1153 28
           6 101 1136 28
           7 253.7 1138 29
           8 541.2 1060 31
           9 530.4 1155 33
           10 793.9 1244 34
           11 1078 1088 35
           12 1125.6 1240 36
           13 1013.5 1135 37
           14 848.2 1318 37
           15 726.7 1074 37
           16 654 1190 38
           17 392.9 1276 38
           18 215.1 1154 37
           19 38.5 1333 35
           20 0 1322 34
           21 0 1269 34
           22 0 1139 33
           23 0 1202 32
           0 0 1291 32];
       Tref=40;
for i=1:length(Solar_env)
       Pgs(i)=(1+(Tref-Solar_env(i,4))*(-5/100))*(Solar_env(i,2)/1000);
end
hour=12;
pgg=Pgs(hour);
for i=1:length(Solar_data)
     PlSS(i)=Solar_data(i,2)*pgg;
end
Total=sum(PlSS)
Ks=1e3;
PL_D=1088;
PL_solar=(30/100)*PL_D; %% Load share by Solar Plant
```

```
% Demand (MW)
Pd=PL_D-PL_solar;
% setting the CSA
LB =data(:,4)';   % Lower bound
UB = data(:,5)';  % Upper bound
pd=10; % Problem dimension (number of decision variables)
N=100; % Flock (population) size
AP=0.00001; % Awareness probability
fl=20; % Flight length (fl)
h1=52.03;
[x]=init(N,pd); % Function for initialization
[xx]=rand(N,length(Solar_data));
[x1]=[xx]<0.5;
Qmin=0;         % Frequency minimum
Qmax=100;        % Frequency maximum
Q=zeros(N,1);   % Frequency
v=zeros(N,pd);   % Velocities
para=[5 10 0.7 0.3 0.9 0.9 0.9];
A0=para(3);      % Loudness  (constant or decreasing)
r0=para(4);      % Pulse rate (constant or decreasing)
sigma=para(5);
alpha=para(6);
zeta=para(7);
iter=0;
A=A0;
r=r0*(1-exp(-zeta*iter));

xn=x;
for i=1:N
S(i)=ceed1(x1(i,:)); % Function for fitness evaluation
F(i)=ceed(x(i,:)); % Function for fitness evaluation
end

mem=x; % Memory initialization
Sol=x;
mem1=x1;
fit_mem=F; % Fitness of memory positions
best=min(F);
fit_mem1=S;

tmax=1000; % Maximum number of iterations (itermax)
for t=1:tmax
  % CROW SEARCH LOOP
   num=ceil(N*rand(1,N)); % Generation of random candidate crows for following
(chasing)
   for i=1:N
       if rand>AP
           xnew(i,:)= x(i,:)+fl*rand*(mem(num(i),:)-x(i,:)); % Generation of a new po-
sition for crow i (state 1)
```

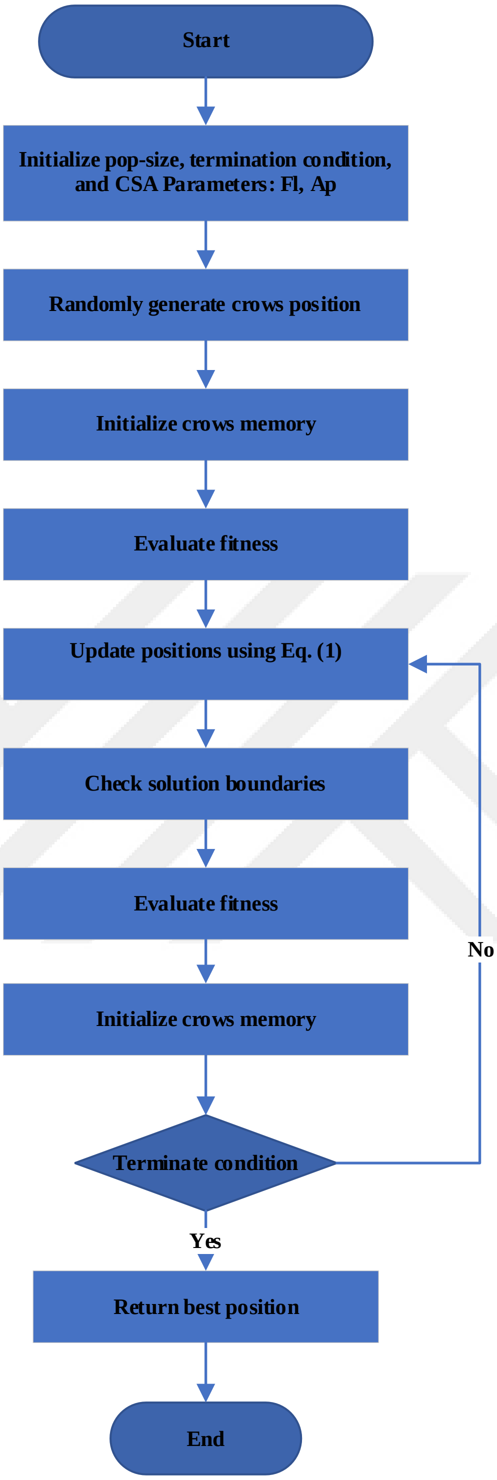
```
        else
            for j=1:pd
                xnew(i,:)=data(j,5)-(data(j,5)-data(j,4))*rand;% Generation of a new posi-
tion for crow i (state 2)
            end
        end
    end

    xn=xnew;
        num=ceil(N*rand(1,N)); % Generation of random candidate crows for follow-
ing (chasing)
    for i=1:N
        if rand>AP
            xnew1(i,:)= x1(i,:)+fl*rand*(mem1(num(i),:)-x1(i,:)); % Generation of a new
position for crow i (state 1)
        else
            for j=1:length(Solar_data)
                xnew1(i,:)=rand;% Generation of a new position for crow i (state 2)
            end
        end
    end

   xn1=xnew1;

for i=1:N
S(i)=ceed1(xn1(i,:)); % Function for fitness evaluation

F(i)=ceed(xn(i,:)); % Function for fitness evaluation

end % Function for fitness evaluation of new solutions

    for i=1:N % Update position and memory
        if xnew(i,:)>=LB & xnew(i,:)<=UB
            x(i,:)=xnew(i,:); % Update position
            if F(i)<fit_mem(i)
                mem(i,:)=xnew(i,:); % Update memory
                fit_mem(i)=F(i);
            end
        end
    end
   for cc=1:N
        for vv=1:length(Solar_data)

            if xnew1(cc,vv)>1
                xn1(cc,vv)=1;
             elseif xnew1(cc,vv)<0
                xn1(cc,vv)=0;
            else
             xn1(cc,vv)=xnew1(cc,vv)<0.5;
```

```
        end
      end
    end

   ffit(t)=min(fit_mem); % Best found value until iteration t
   ffit1(t)=min(fit_mem1); % Best found value until iteration t
   a(t)= min(fit_mem);
   aa(t)= min(fit_mem1);
end

ngbest=find(fit_mem== min(fit_mem));
ngbest1=find(fit_mem1== min(fit_mem1));
g_best=mem(ngbest,:); % Solutin of the problem
g_best1=mem1(ngbest1,:); % Solutin of the problem
P1=g_best
Pl_S=g_best1
pgg=Pgs(hour)
Pl_S1=pgg*g_best1.*transpose(Solar_data(:,2))
PL=P1*B*P1'
Popt=sum(P1)+sum(Pl_S1)
n=length(data(:,1));
for i=1:n
    F1(i)=data(i,1)*
P1(i)^2+data(i,2)*P1(i)+data(i,3)+(data(i,6)*sin(data(i,7)*(data(i,4)-P1(i))));
    E1(i)=data1(i,1)*
P1(i)^2+data1(i,2)*P1(i)+data1(i,3)+(data1(i,6)*exp(data1(i,7)*P1(i)));
end
n=length(Solar_data(:,1));
for i=1:n
    S1(i)=Solar_data(i,3)* Solar_data(i,2)*Pl_S(i)*pgg+ Ks*(Solar_data(i,2)-
Solar_data(i,2)*Pl_S(i)*pgg);
end
Fuel=sum(F1)
Emmission=sum(E1)
Solar=sum(S1)
CEED=Fuel+h1*Emmission+Solar
plot(a+aa)
toc

function s=simplebounds(s,Lb,Ub)
  % Apply the lower bound vector
  ns_tmp=s;
  I=ns_tmp<Lb;
  ns_tmp(I)=Lb(I);
    % Apply the upper bound vector
  J=ns_tmp>Ub;
  ns_tmp(J)=Ub(J);
  % Update this new move
  s=ns_tmp;
```

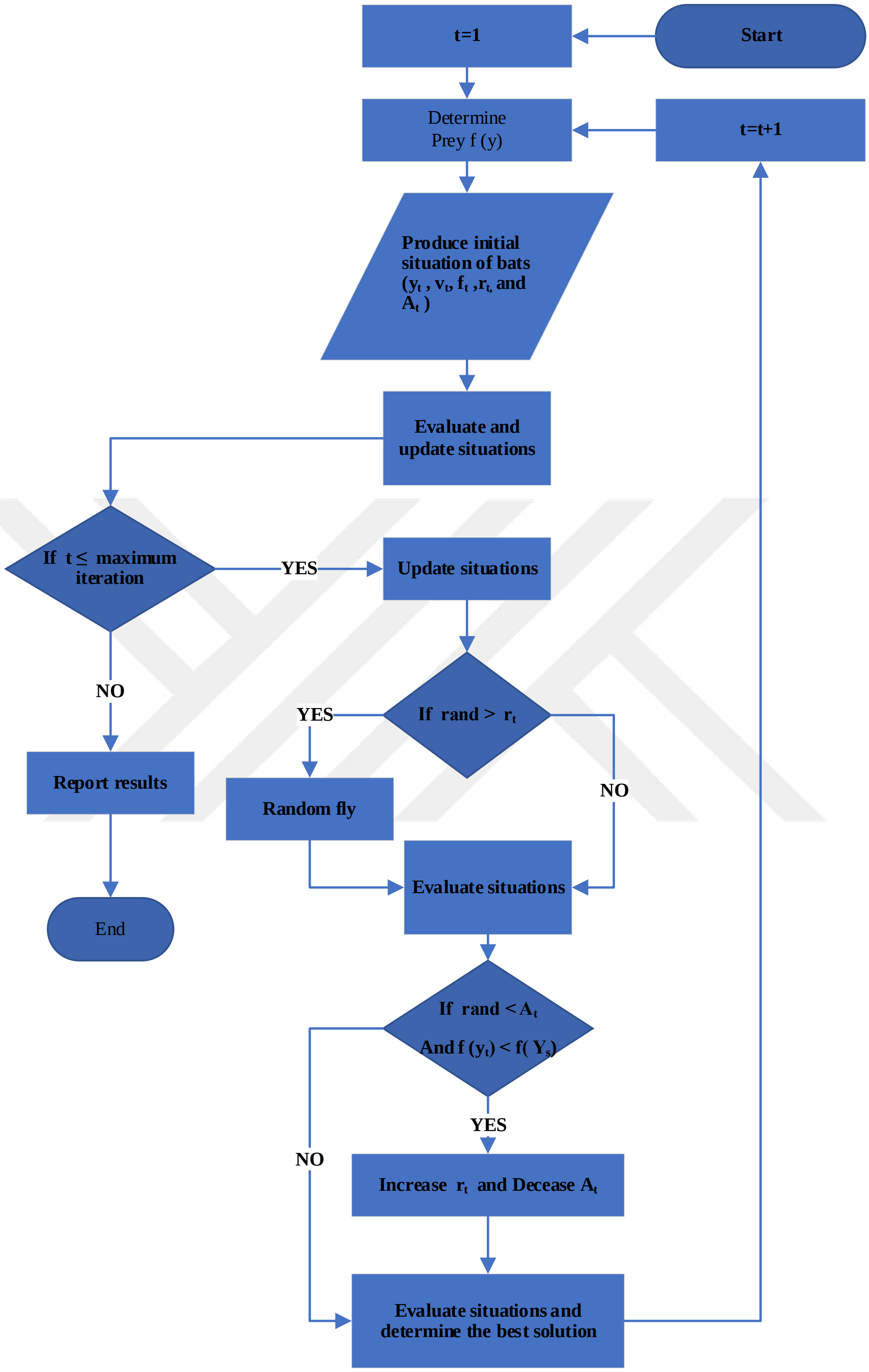
```
end
```

APPENDIX B.

FLOWCHART FROM ALGORITHMS



Flowchart of Crow Search Algorithm



Flowchart of Bat Search Algorithm.

APPENDIX C.

PUBLICATIONS

Articles Published in Journals

INTERNATIONAL JOURNAL of RENEWABLE ENERGY RESEARCH
A. Elbaz and M. Tahir Güneşer, Vol.11, No.1, March, 2021

Multi-objective Optimization of Combined Economic Emission Dispatch Problem in Solar PV Energy Using a Hybrid Bat-Crow Search Algorithm

Abdurazaq Elbaz *‡, Muhammet Tahir Güneşer *

* Department of Electrical & Electronics Engineering, Karabuk University, Demir Celik Campus, Karabuk, Turkiye

(abdalrazaklabz@gmail.com, mtguneser@karabuk.edu.tr)

‡ Corresponding Author; Postal address: Engineering Faculty, Karabuk University, Demir Celik Campus, 78100, Karabuk, Turkiye; Tel: +90 370 418 8860; abdalrazaklabz@gmail.com

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Abstract- This paper deals with the multi-objective fuel cost optimization of a conventional power plant (CPP) and emission minimization in CPPs and solar PV power plants (SPVPPs) using a hybrid bat-crow search algorithm. To resolve this complicated, non-convex, and excessively nonlinear problem, a variety of meta-heuristic optimization algorithms are developed and effectively employed. To handle evolutionary multi-objective algorithms' inadequacies, such as early convergences, slowly meeting the Pareto-optimal front, and narrow trapping, applying a combination of different algorithms is unusual.

This paper offers a hybrid evolutionary multi-objective optimization process based on combining the crow search optimization with the bat algorithm for dealing with the combined economic emission dispatch problem for SPVPPs. A hybrid technique combined with the proposed constriction handling method can balance exploitation and exploration tasks. Different IEEE standard bus systems were tested with the proposed hybrid method using the quadratic cost function and monitoring the transmission losses. The results of the proposed algorithm have also been compared with those of the bat, PSO, and crow search algorithms. The proposed method can be said to be effective considering the simulation results.

Keywords Bat algorithm, Multi-objective optimization, Crow search algorithm, Combined economic emission dispatch.

1. Introduction

It is important to optimize power system costs and protect the atmosphere from greenhouse gas emissions, and algorithms for these aims are also important. For the mentioned purposes, an appropriate algorithm may assure the best active power scheduling to concurrently reduce fuel costs and emissions of conventional fossil fuel-powered power generation plants [1]. This can also make it possible to attain great financial gains [2] and reduce dangerous emissions including nitrogen oxide (NO_x), sulfur oxide (SO_x), and carbon dioxide (CO_2). Since the objectives mentioned here are contradictory, they can create multi-objective combined economic emission dispatch (CEED) issues, which are resolvable through traditional numerical programming processes like gradient search and lambda iteration, or even through modern heuristic optimization methods. Resolving these CEED issues has benefits if heuristic optimization methods are used rather than using traditional population-based numerical programming methods. A heuristic method does not need mathematical data or gradient information for its searches. It uses stochastic operators for searching, and it is flexible and straightforward to implement. It has an inherently scalable parallel structural design and, additionally, it proceeds quickly while making calculations [2].

It is not possible to obtain a single best result to solve such multi-objective CEED problems since we are struggling to achieve contradictory objectives in these cases, such as emission reduction and fuel cost optimization. In this context, contradictory objectives are concurrently minimized for the multi-objective optimization problem to approach a transactional. This requires further processing to obtain a single favored outcome. The literature shows the application of domination-based structures through multi-objective evolutionary algorithms that reduce the emissions and fuel costs while resolving the CEED problem. The mentioned population-based approaches result in simultaneous numerous non-dominant outcomes [3]. Such non-dominant outcomes

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ORIGINAL ARTICLE

Multi-Objective Optimization Method for Proper Configuration of Grid-Connected PV-Wind Hybrid System in Terms of Ecological Effects, Outlay, and Reliability

Abdurazaq Elbaz[1] · **Muhammet Tahir Guneser**[1]

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Abstract
The assessment of the performance of grid hybrid frameworks depends primarily on the costs and reliability, associated with reduced greenhouse gas (GHG) emissions of the system. In this work, with objectives based on the minimization of two optimization features, namely loss of power supply probability (LPSP) and cost of energy (COE), multi-objective optimization of a grid-connected PV/wind turbine framework was implemented in the Faculty of Engineering in Gharyan, Libya, with the aim of providing adequate electricity, while optimizing the system's renewable energy fraction (REF) was the third objective. This research also aimed to estimate the resulting amount of power produced by the hybrid system and mathematical models were submitted. The results showed the share of the total energy supplying the electricity demand for each part of the network. This study subsequently explored the interrelationship of the grid and the proposed hybrid system in relation to the capacity of the network to sell or obtain electricity from the hybrid system. In addition, multi-objective bat algorithm (MOBA) findings were divided into three dominant regions: the first region was the economically optimal solution (lowest COE), the second region was the conceptual perspective of utilizing renewable energies (highest REF), and the final region was the optimal solution with optimal environmental effects (lowest GHG emissions).

Keywords GHG emission · Cost of energy · Renewable energy fraction · Multi-objective · Grid-connected · PV

1 Introduction

The current continual increase in the demand for electricity and the rapid decline in conventional energy resources has required an imperative search for renewable energies as alternative energy sources. In this process, PV solar and wind power have been identified as the most viable sources of electricity with the ongoing growth of the market with solar power from multiple clean energy sources. Moreover, the penetration rates of PV systems are high at present, and the usage of PV cells and advanced electronic technologies is expected to grow globally. Furthermore, wind power is known as the most significant and exciting form of renewable energy because it is efficient, universal, and of high capacity. On the other hand, wind and PV energy still do not provide full confidence and they have certain disadvantages, such as vulnerability to unpredicted natural conditions and enormous dependence on variations in environmental conditions like sunlight and wind speed. Therefore, a mixture of PV energy and wind energy can mitigate individual variances in PV as well as wind hybrid power generation networks, improve overall power capacity, and provide greater efficiency, which is associated with better quality for the electricity grid [1, 2].

Particularly in mountainous regions and rural areas where systems might be installed close to demand areas, renewable energy has proven to be the optimal solution for deploying micro-networks, thereby removing the need for traditional electricity grids [3–6]. Likewise, on-grid and off-grid renewable energy frameworks have been created. Overall, the question of the possible utilization of renewable energy sources is solved via many different energy supplies where they depend entirely upon unpredictable environmental conditions, which are not completely specified in terms

✉ Abdurazaq Elbaz
abdalrazaklabz@gmail.com

Muhammet Tahir Guneser
mtguneser@karabuk.edu.t

1 Department of Electrical and Electronic Engineering, Karabuk University, Karabuk 78100, Turkey

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Original scientific paper

Algorithms to Model and Optimize a Stand-Alone Photovoltaic-Diesel-Battery System: An Application in Rural Libya

Abdurazaq ELBAZ*, Muhammet TAHIR GUNESER

Abstract: This paper introduces a new optimum calculation technique for a stand-alone hybrid photovoltaic-diesel-battery system (PDBS), which meets the energy requirements of a small village in southern Libya. The bat algorithm design strategy is applied to reduce the annual cost of the system, taking into consideration the controlled electricity restriction and the optimal numbers of PV panels, diesel generators, and batteries. Comparative tests are performed using MATLAB for the bat algorithm with the grey wolf search algorithm and particle swarm optimization, demonstrating that the bat algorithm determines the optimum size of the PDBS effectively at a lower expense. Results then indicate that, taking into account the reliability characteristics, this has a significant effect on optimum capacity, load supply, and cost.

Keywords: annual system cost; bat algorithm; grey wolf optimization algorithm; particle swarm optimization algorithm; photovoltaic-diesel-battery system

1 INTRODUCTION

There is a need for sustainable power sources in remote rural areas, which rely on the national power grid for their power needs. So far, solar photovoltaic (PV) energy has been beneficial because it is sustainable, it does not require complicated maintenance, and, above all, it does not release greenhouse gases. Thus, experts in several countries have recommended PV systems because they complement the national grid; however, PV systems have a fundamental problem, which is their discontinuous power flow because solar energy varies with seasonal and weather changes in the sunlight. To make the power flow reliable, hybrid systems are generally equipped with PV arrays and different types of generators [1-3].

Hybrid photovoltaic-diesel-battery devices have been suggested for this reason in rural Libya in previous research since they seem appropriate for satisfying the regular energy requirements. Such a hybrid system uses a battery bank for storing excessive power that PV arrays generate to meet the night-time needs. In this system, a diesel generator is added to overcome the unevenness of the generated power [4, 5]. Thus, a PV-diesel system offers more excellent power generation reliability as compared to PV-only or diesel-only systems. In a nutshell, hybrid systems offer more flexibility, efficiency, and cost-savings.

Moreover, when a battery and a backup diesel generator are combined with a PV system, it substantially reduces the operational costs and pollutants [6, 7]. When a PV-diesel-battery system is first implemented, it results in higher equipment costs; however, if we avoid this initial investment/cost, we will have to adopt a sub-optimal design, which has a negative economic impact in the long run [8]. Thus, the complications of the optimal design of a hybrid renewable energy system should be embraced because classical designs can be either active or efficient, but not both at the same time [9]. In the last 20 years, meta-heuristic optimization methods have become widespread. Some, including ant colony optimization [10], genetic algorithms [11], grey wolf optimization (GWO) [12], and particle swarm optimization (PSO) [13], are still popular among experts in different fields. They are commonly applied and easy-to-implement techniques because they are straightforward, flexible, and derivation-free. The mentioned methods each have their own benefits, which sometimes make them good choices to solve optimization issues, and they are based on natural phenomena, which make them useful and straightforward. This implies that the meta-heuristic process might yield useful outcomes in some cases; however, they are likely to show poor performance in more demanding situations. Therefore, researchers have made efforts to propose and test a new algorithm to assure hybrid sustainable power supplies [13, 14].

The bat algorithm is a concept based on the echo location of bats (or microbats). Yang developed it in 2010, and it gradually became a frequently used technique because it offers a diversity of solutions. It also uses automatic zooming for balancing exploitation and exploration that mimics different pulse emissions of bats when they search for their prey. Consequently, it is beneficial and it starts quickly [15]. Since it is meta-heuristic in nature, a bat algorithm has "microbats" that use echoes with changing frequency, loudness, and pulse rates during the "random walk" process. In this case, it is possible to reach the best solution when optimization ends. This process can be applied to solve real-world problems by optimizing objective functions. In this form of optimization, the number and types of PV panels and batteries are limited. As soon as the iteration begins, it generates a random value for the battery modules with PV panel type in kilowatts, which is computed and saved as a fitness value. As the iteration loops continue, new bats are selected from the existing bats, which means that new modules and types of power generation are chosen. When the parent and offspring bats' fitness values are compared, we choose the best bat for decreasing the cost; therefore, this approach is used in various industrial and engineering applications to optimize real-world issues [16].

The use of the unstable bat algorithm to solve economic dispatch problems containing a variety of equity and discrimination restrictions, like the forbidden operational areas of the power balance and the ramp rate cap, has been demonstrated in the literature. Most research has also verified that the bat algorithm is simple to execute and delivers good performance. In this respect, this algorithm is proposed and applied in this study to determine the perfect size for a stand-alone hybrid

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Optimal Sizing of a Renewable Energy Hybrid System in Libya Using Integrated Crow and Particle Swarm Algorithms

Abdurazaq Elbaz*, Muhammet Tahir Güneşer

Karabuk University, Engineering Faculty, Eletrical and Electronics Department, Karabuk, 78100, Turkey

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ABSTRACT

Sizing optimization should be used to design an efficient, sustainable, and feasible hybrid system. In this paper, a hybrid power plant consisting of an off-grid photovoltaic and wind energy system was planned to supply the demand of residential houses in Libya. To minimize installation and operational costs by sizing each part of the hybrid system, the crow search technique was applied. We optimized the number of photovoltaic modules, wind turbine power, and battery capacity and then we compared the performance of the crow algorithm with the particle swarm optimization algorithm for hybrid system design. The results of the crow algorithm suggest better efficiency for sizing lower-cost hybrid power plants consisting of photovoltaic and wind systems.

1. Introduction

Renewable energy systems are basically designed to achieve two objectives: cost-effectiveness and environmental protection. It is possible to achieve these objectives by reducing both dangerous emissions and fuel costs. This type of power system has clear financial benefits [1] other than reducing emissions of carbon dioxide (CO_2), nitrogen oxide (NOx), and sulfur oxide (SOx), which can be detrimental for life on this planet [2]. Whenever these objectives are pursued at the same time, the combined economic emission dispatch (CEED) problem emerges, which can be addressed through traditional mathematical methods like lambda iteration, gradient search, and optimization through modern heuristics [1]. However, in this case, it is not possible to solve the CEED problem because the procedure does not give a single result. Additionally, for achieving two contradictory aims, such as reduction of both pollution and fuel costs, mathematical/gradient information is not required. On the contrary, this optimization problem needs some kind of transactional solution like the Pareto optimal (PO) solution [3], requiring further processing for finding the best optimized and most favorable solution. The literature shows that some multi-objective algorithms help reduce greenhouse gases while decreasing fuel costs at the same time. These algorithms include scatter search [4], the bacterial foraging algorithm [5], particle swarm optimization [6], teaching-learning-based optimization [7], the harmony search algorithm [8], and differential evolution [9]. We have tested different methods to solve the non-convex and non-linear CEED problem.

In this case, the "h" parameter is used to handle dimensional problems that can be solved through the sketched evolutionary algorithm [8]-[10]. We can also solve the CEED problem without using the mentioned parameter by regularizing fuel costs and pollutants. This is possible using evolutionary algorithms (EAs) by solving a single objective function, but such methods have a shortcoming: researchers need to make repeated efforts to find the objective solution.

Results show that hybrid algorithms are useful and efficient in performing parallel processing. For achieving the best solution, a balance is required between exploration and exploitation. While exploration is pivotal for any kind of algorithm, exploitation helps in finding excellent solutions. The present research involves bat [11] and crow [12]algorithms for solving the CEED issue. We have selected a hybrid structure that combines the properties of crow search and bat algorithms and resolves the problems of the mentioned population-based methods. Hybridization was also chosen because it gives more diverse and acceptable solutions.

2. Types of Algorithms

2.1. Particle Swarm Optimization (PSO)

Potential solutions, which are also referred to as "particles," lie within the problem space. Here, "swarms" means the multi-dimensional modeling spaces in which the particles exist, and they

*Corresponding Author: Abdurazaq Elbaz, Email: abdalrazaklabz@gmail.com

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Chapter of Book

Applications of Nature-Inspired Computing in Renewable Energy Systems

Mohamed Arezki Mellal
M'Hamed Bougara University, Algeria

A volume in the Advances in Environmental Engineering and Green Technologies (AEEGT) Book Series

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Chapter 8

Hybrid Optimization Methods Application on Sizing and Solving the Economic Dispatch Problems of Hybrid Renewable Power Systems

Muhammet Tahir Guneser
https://orcid.org/0000-0003-3502-2034
Karabuk University, Turkey

Abdurazaq Elbaz
Karabuk University, Turkey

Cihat Seker
Karabuk University, Turkey

ABSTRACT

Renewable energy systems are spread all over the world due to the security problems encountered in accessing fossil fuels, the desire to reduce the environmental damage and to respond to the rapid increase in energy demand. However, the problems are experienced in renewable energy technologies in sustainable supply and reduction of production costs. Obtaining the optimum power distribution planning between photovoltaic, wind, biomass, and other systems depending on the relevant parameters and optimizing the distribution of energy supply-demand planning among the same sources can be applied as an effective solution by using several single optimization methods or new updated hybrid versions of them. In this chapter, common methods were evaluated and an application of crow and particle swarm as a hybrid method was examined in a certain region of Libya for a PV/wind hybrid renewable power system.

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Refereed Congress / Symposium publications in Proceedings

IRENEC 2018

IRENEC

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The College of Science and Engineering (CSE) and Organizing
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held by Hamad Bin Khalifa University, Qatar

Using BAT Algotirhms for Techno-economic Analysis of Grid-Connected PV Systems and Comparison with PSO and WOA methods

Abdurazaq Elbaz, Muhammet Tahir Guneser

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Affiliation: Karabuk university, Turkey

This is to certify that ***Student ABDURAZAQ ELBAZ*** presented the above-mentioned paper at the ***12th International Renewable Energy Congress*** **"IREC 2021"** organized virtually on October 26th – 28th, 2021.

The paper has been published in the congress proceedings.

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HAS ATTENDED AND PRESENTED A PAPER ENTITLED

Optimization of Grid Connected Solar Power System Capability by Using Hybrid Algorithms of Bat and Bee Colony

AT THE INTERNATIONAL CONFERENCE ON RENEWABLE ENERGY 2020 ORGANIZED BY PREMC FROM NOVEMEBER 25TH TO NOVEMBER 27TH ONLINE.
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RESUME

Abdurazaq Elbaz He completed primary and elementary education in Ghiryin, of Libya. In 2009, he graduated from Electrical and Electronic Engineering Department, Faculty of Engineering, AL-jabaL AL-gharbi University Ghiryin. After that, he worked as a full-time researcher at Center for Solar Energy Research and Studies in the period 2009 to up to now. In 2013, he got his MSc degree in Electrical and Electronic Engineering Tripoli University-Libya. In the period 2015-2016, he worked as part-time lecturer in some institutes in Libya. In 2013, he got his MSc degree in Electrical and Electronic Engineering Tripoli University-Libya.

In 2013, he got his MSc degree in Electrical and Electronic Engineering Tripoli University-Libya. In 2017, he got a scholarship to continue his PhD education in Turkey. He started his PhD academic program at Karabuk University, registered in Department of Electrical and Electronic Engineering and started his PhD thesis research. His research area focuses on renewable energy systems.