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An Improved Multicriteria Optimization Method for Solving the Electric Vehicles Planning Issue in Smart Grids via Green Energy Sources

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ABSTRACT In the given research, a new multicriterion (multiobjective) optimization algorithm has been considered to solve the problem of electric vehicles (EV) scheduling in a smart network in view of sustainable energy sources based on the cost and pollution minimization. By considering the environmental and economic problems, the application of EVs as a proper charging/discharging scheduling model and green energy sources plays an important role in the power system. This study focuses on multicriteria scheduling through uncertainty factors via inexhaustible assets and EVs, presenting a battery storing framework and reducing both the operation costs and the amount of the framework's pollution while improving the procedures. For this purpose, a new optimization algorithm has been considered to address the mentioned problem taking into account some clean energy sources and emission. The proposed model is examined in smart grid environment based on real-life model by Demand Response Program (DRP) evaluation and the uncertainties in sustainable energies. The proposed optimization algorithm shows more desirable results in comparison with other models, while the efficiency of the suggested approach is studied and evaluated in two power systems, i.e., a 33-bus standard power system and a 94-bus Portugal network. The obtained results validate the proposed method.

INDEX TERMS Multi-criteria optimization, electric vehicles planning, smart grid (SG), renewable energy sources.

NOMENCLATURE

EVs	Electric Vehicles
SG	Smart Grid
DRP	Demand Response Program
PEVs	Plug-in Electric Vehicles
DG	Distribution Generation
BIBC	Bus-Injection to Branch-Current
BCBV	Branch-Current to Bus-Voltage
CS	Cuckoo Search
MCCS	Multi-Criteria Cuckoo Search
UCGA	Uncontrolled Classifying Genetic Algorithm
IMCCS	Improved MCCS
GA	Genetic Algorithm
EV	Differential Evolution
ACO	Ant Colony
PSO	Particle Swarm Optimization
$[B]$	Branch current vector of each bus
$[I]$	Current injections of each bus
$[V_0]$	Initial voltage vector of the bus bars
$[V]$	Voltage vector of the bus bars
Vci	Cut-in speed of
Vco	Cut-out speed
Pr	Power
Vr	Rated wind speed

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SWi	Specific speed of the wind
η^{PV}	Solar cells coefficient
S^{PV}	Total surface area of the solar cells in the solar energy plant
$F1$	Overall expenditure of exploitation with DG
$C_{FC,Diesel(DG)}$	Diesel generator
$C_{DG(DG,t)}$	The cost of the DG generation in time t
$P_{DG(DG,t)}$	Dynamic energy production of Foucelle and Diesel DG_S.
a, b, and c	Coefficients of the fuselage and diesel producers' costs are.
$u_{(DG,t)}$	Binary variable
$C_{Wind(DG)}$	The cost of the wind turbine exploitation
$C_{PV(DG)}$	The cost of solar cell exploitation
$P_{DG(wind,t)}$	The generative energy of the wind unit
λ_{wind}	The coefficient of the wind turbine exploitation cost
$P_{DG(PV,t)}$	The generative energy of the solar unit
β_{PV}	The coefficient of the wind solar cells cost.
$F2$	Cost related to the energy purchased from the grid
P_{sub}^{max}	Maximum of the activated energy from the main post.
Dt	The demand of the entire network in time t
$Loss_t$	The loss of the entire network in time t
$E_{CO2}^{DG,t}$	Carbon dioxide emission rate in unsustainable DGs
$P_{Grid(t)}$	Active energy required by the grid
$C_{Grid(t)}$	Energy price of the grid in time t.
$F3$	Cost of charging and discharging the electric vehicles
$P_{Discharge(V,t)}$	The discharge energy of the v^{th} vehicle
$P_{Charge(V,t)}$	The charge energy of the v^{th} vehicle
$C_{Discharge(V,t)}$	The energy cost of discharging the v^{th} vehicle
$C_{Charge(V,t)}$	The energy cost of charging the v^{th} vehicle in time t
$P_{Stored(V,t)}$	The stored energy of vehicle V in time t
N_V	The number of electric vehicles
$P_{DischargeLimit(V,t)}$	The constraint of discharging vehicle V in time t
P_{DG}^{max}	The maximum authorized energy for each DG
P_{DG}^{min}	Minimum energy allowed for each DG
$D(i)$	Demand for electricity
$P(i)$	Cost of consumed electricity

I. INTRODUCTION

Reducing fossil fuel sources, stringent policies on reducing environmental pollution, the costly establishment of new infrastructure in the existing energy network, current network low effectiveness, requirements for improving the quality of power, requirements for increasing supply security, the widespread and growing impact of sustainable energy sources, the development of Electric Vehicles (EVs), etc., are all stimulators that play a decisive role in converting the existing energy network into an intelligent network. The intelligent network is faced with an increasing growth of dispersed energy resources, such as dispersed generation resources, load controlling, storing systems, and EVs. Managing these resources requires effective managing methods that can keep the consistency of the energy network at an acceptable level [1].

The intelligent grid concept could serve as a bridge between the current traditional grid and the future active grid with flexible generation and consumption. This notion could be attributed to some capabilities of the intelligent grid, such as maximizing the use of sustainable energies and creating a widespread communication framework between the operator and the consumer [2].

Electric vehicles have been introduced as a solution to the paucity of fossil fuels and air pollution. The spread of electric vehicles connected to the power grid may bring about many technical deficiencies that require appropriate examination. In the short term, the majority of EVs will add a large amount of energy request to the network. However, Plug-in Electric Vehicles (PEVs) can reduce the emissions of pollutants in the shipping industry. The aim is to decrease emissions by optimally utilizing electric vehicles as energy storage devices in a combined energy system with sustainable energy sources [3], [4].

In this paper, a multicriterion planning of energy resources is proposed with the aim of achieving the aforementioned goals. In this scheduling, the charge in the exploitation and the level of pollution of the distribution grid are concurrently decreased to the greatest extent possible. An acceptable response could be found by this planning utilization to meet all the goals. Additionally, we bring the proposed model closer to the real-life model by Demand Response Program (DRP) evaluation and the uncertainties in the sustainable energies [5]. To achieve this goal, several steps and scenarios have been designed, such as: the load network is performed without energy resources, the grid is programmed in the presence of sustainable resources and EVs through cost and pollution minimization, and the DRP is considered in the network. Accordingly, the contributions of this paper can be summarized as follows:

1) The application of a new multicriteria algorithm is proposed over the mentioned power system energy resource programming.

2) The proposed power system problem is solved by considering the sustainable energy sources through the minimization of cost and pollution.

3) Application of DRP to the proposed problem.

4) Application of the proposed solution model to two different test cases, considering various scenarios.

The remainder of paper is organized as follows: Section 2 presents the energy resource programming, Section 3 introduces the proposed optimization algorithm, Section 4 presents the numerical results and analysis, and Section 5 concludes the paper.

II. MODELING OF ENERGY RESOURCES PROGRAMMING

In this study, the intelligent optimization algorithm utilizes multicriteria programming through simultaneous consideration of unsustainable resources (fuel cell and diesel generator), sustainable resources (wind and solar) and PEVs. In this case, the exploitation cost (as the cost of purchasing the energy from the grid, the cost of dispersed products and the cost of charging and discharging the cars) and the amount of carbon dioxide emissions (including emissions from the power grid, dispersed unsustainable resources, such as fuel cell and diesel producers) serve as the two objective functions of the problem. With regard to the notion that the electric vehicles studied in the current research are PEVs, both charging and discharging are considered [5].

A. LOAD DISTRIBUTION

In a normal distribution system, load distribution is simple, and the direction is from the producer to the consumer. However, connecting the Distribution Generation (DG) to the grid, the load stream becomes further difficult. Normally, the analysis of the non-uniform distribution system is more complicated and cumbersome than the analysis of a uniform system. The load distribution method in this study is established in accordance with Bus-Injection to Branch-Current (BIBC) and Branch-Current to Bus-Voltage (BCBV), which are two matrices that represent the relationship between the bus current injections and branch currents and the association between the branch currents and bus potential differences, respectively. These two matrices provide a new expression on the association between the bus bar potential difference, the flow of branches, and the injectable flow of bus bars. Here, these two matrices are used to present the load distribution solution process [6]. Relation (1) is implemented to reveal the association among the injection current and the branch current:

$$[B] = [BIBC]\,[I] \tag{1}$$

In the relation (1-3), $[B]$ and $[I]$ are the branch current vector and current injections of each bus, respectively. The stationary matrix is a triangular top matrix and consists of only non-zero elements. This matrix is constructed via the subsequent algorithm:

1) In terms of a distribution network by m branches as well as n buses, the matrix dimension is equal to: $(m(n-1))$

2) If branch l is among buses i and j, all the columns of i^{th} bus would copy the BIBC matrix into the j^{th} column. The row entry of the l^{th} branch and the j^{th} bus column is supposed to be $+1$.

3) The second step is performed again until all branches of the BIBC matrix are examined [7].

Equation (2) represents the relationship between the branch current and the bus bar voltage:

$$[V_0] - [V] = [BCBV]\,[B] \tag{2}$$

In this relation, $[V_0]$ and $[V]$ correspond to the initial voltage vector of the bus bars and the voltage vector of the bus bars, respectively. Relation (3) can be altered as follows:

$$[\Delta V] = [BCBV]\,[B] \tag{3}$$

In relation (3), $[\Delta V]$ is as follows:

$$[\Delta V] = [V_0] - [V] \tag{4}$$

The fixed matrix contains non-zero entries with the impedance of the lines, which consists of three stages:

1. In terms of a distribution grid with m branches and n bus bars, the Branch-Current to Bus-Voltage (BCBV) matrix dimension is equal to $((n-1)m)$:

2. Under the condition that branch l is between bus bars i and j, all the rows of the i^{th} bar would copy the BCBV matrix into the j^{th} rows. The row entry of the j^{th} bus l^{th} branch column are equivalent to the line resistance of Z_{ij}

3. The second step is performed again until all branches of the matrix are examined.

It can be said that the BIBC and BCBV matrices are constructed based on the structure of the grid topology. The BIBC matrix shows a relationship between the bus current injections and branch currents. In other words, corresponding changes in the branch's current cause a change in the bus current injections, which can be directly changed by the BIBC matrix. The BCBV matrix represents the relationship between the branch currents and bus voltages. In other words, the corresponding changes in the bus voltage cause a change in the current of the branches, which could be calculated directly by the BCBV matrix. A combination of (1) and (3) would lead to achieving the association between the bus potential difference and the bus current injections:

$$[\Delta V] = [BCBV]\,[BIBC]\,[I] = [DLF]\,[I] \tag{5}$$

In conclusion, according to the description given, the load distribution of the irradiation distribution system can be calculated through the iteration method as per (6):

$$\begin{aligned} I_i^k &= I_i^{re}\left(V_i^k\right) + j\,I_j^{im}\left(V_i^k\right) = \left(\frac{P_i + jQ_i}{V_i^k}\right)^* \\ \left[\Delta V^{k+1}\right] &= [DLF]\left[I^k\right] \\ \left[V^{k+1}\right] &= [V_0] + \left[\Delta V^{k+1}\right] \end{aligned} \tag{6}$$

In the above relations, k represents the number of related iterations [7], [8].

B. LOSS EQUATION

The active loss equation in the irradiation distribution network is described based on actual current and resistance of the lines, the reactive losses using the wattles current and the reactance of the lines through (7) and (8):

$$P_{Loss} = \left[B^2\right][R_{line}] \tag{7}$$

$$Q_{Loss} = \left[B^2\right][X_{line}] \tag{8}$$

C. WIND POWER MODELLING

The alteration in the wind power is dependent on the wind speed in the wind farm. The power output of a turbine can be determined from the power curvature of the graph, whose output power is based on the wind speed. The turbine is designed in such a way that starts to generate power at a cut-in speed of V_{ci} and it will turn off at a cut-out speed V_{co} for safety reasons. The rated power P_r is produced when the wind speed is produced between the rated wind speed V_r and the cut-out speed V_{co}. The generated power P_i that is appropriate to the specific speed of the wind SW_i is determined by the following equation [9]:

$$P_i = \begin{cases} 0 & 0 \leq SW_i \leq V_{ci} \\ P_r \times (A + B \times SW_i + C \times SW_i^2) & V_{ci} \leq SW_i \leq V_r \\ P_r & V_r \leq SW_i \leq V_{co} \\ 0 & SW_i \geq V_{co} \end{cases} \tag{9}$$

The procedure for calculating the constants of A, B and C could be calculated as described in [10]. In the current study, the typical model of wind power has been used for a cut-in speed of 4 m/s, a rated speed of 14 m/s, a cut-out speed of 25 m/s and an extreme power production of 1 MW.

D. MODELLING THE ENERGY FROM THE SUN

The production energy of solar cells is mainly influenced by the solar irradiance on their surface. The distribution of the output power of solar cells is calculated based on the radiation distribution and as function of converting the radiation to electrical power. The radiation-to-power conversion function used in this study is based on the relationship offered in the following equation [11]:

$$P = \eta^{PV} \times S^{PV} \times g \tag{10}$$

In the above equation, η^{PV} represents the solar cells and S^{PV} represents the total surface area of the solar cells in the solar energy plant. The amount of solar radiation is signified through g.

E. OBJECTIVE FUNCTIONS

In forming the problem of energy resources scheduling in an intelligent distribution network, at the beginning the irradiation load distribution is performed, which is based on relation (7), and the grid losses are calculated. The study period in this article is a day. So, the goal is to reduce both functions by considering the constrains in solving the problem of intelligent distribution grid planning to the greatest extent possible. The multicriteria optimization function is described as follows [12]–[14]:

$$\text{Minimize}\left\{\mathrm{F}^{\mathrm{Cost}}, \mathrm{F}^{\mathrm{Emission}}\right\} \tag{11}$$

F. COST FUNCTION

The cost of the total distribution of the grid exploitation in the presence of EVs, dispersed outputs and demand response is calculated through the following planned method [15]:

$$F^{Cost} = F1 + F2 + F3 \tag{12}$$

Function *F1* represents the overall expenditure of exploitation with *DG*. This function consists of 3 constituents. The first constituent is related to the costs of the fuselage and diesel generator, the second constituent is the cost of the wind energy farm exploitation, and the third constituent is the cost of the solar cell exploitation:

$$F1 = C_{FC,\mathrm{Diesel}\,(DG)} + C_{W\,\mathrm{ind}\,(DG)} + C_{PV(DG)} \tag{13}$$

In relation (13), the cost of the exploitation of the fuselage units and the diesel generator is represented through $C_{FC,Diesel(DG)}$. In terms of the issue of programming the energy sources in the intelligent distribution grid, according to the second step in (6), the unsustainable resources are added to the grid. The coefficient of the dispersed output power is assumed to be 1, so only the dynamic energy will be noticed in the relations. In this matter, the function involves only the cost of unsustainable resources exploitation [15]:

$$C_{FC,\mathrm{Diesel}(DG)} = \sum_{t=1}^{T}\sum_{DG=1}^{N_{DG}} P_{DG(DG,t)} \times C_{DG(DG,t)} \quad \forall t \in \{1, \ldots, T\} \tag{14}$$

$$C_{DG(DG,t)} = a_{DG} \times u_{(DG,t)} + b_{DG} \times P_{DG(DG,t)} + c_{DG} \times P^2_{DG(DG,t)} \tag{15}$$

The cost of the DG generation in time t is designated as $C_{DG(DG,t)}$.

Dynamic energy production of Foucelle and Diesel $\mathrm{DG_S}$ is signified through $P_{DG(DG,t)}$.

The coefficients of the fuselage and diesel producers' costs are a, b, and c. In addition, $u_{(DG,t)}$ signifies the binary variable that represents either being in orbit or being DG when the mode is 1 and 0, respectively.

Under the condition that the sustainable resources (wind and solar) are added to the problem of intelligent distribution grid programming, the cost of exploiting these resources is added at the expense of unsustainable products. In this case, two units of the fuselage and diesel generator are replaced by the wind energy plant and solar cell. The wind turbines are situated at bus bar 19 and the solar cells are situated at bus bar 27.

The cost of the wind turbine exploitation $C_{Wind(DG)}$ and the cost of solar cell exploitation $C_{PV(DG)}$ are calculated via (16) and (17), respectively:

$$C_{Wind(DG)} = \sum_{t=1}^{T} \sum_{wind=1}^{N_{wind}} \lambda_{wind(t)} \times P_{DG(wind,t)} \tag{16}$$

$$C_{PV(DG)} = \sum_{t=1}^{T} \sum_{pv=1}^{N_{pv}} \beta_{PV(t)} \times P_{DG(PV,t)} \tag{17}$$

The generative energy of the wind unit is represented through $P_{DG(wind,t)}$;

The coefficient of the wind turbine exploitation cost is signified through λ_{wind};

The generative energy of the solar unit is denoted by $P_{DG(PV,t)}$;

The coefficient of the wind solar cells cost is signified through β_{PV}.

Function $F2$ represents the cost related to the energy purchased from the grid as follows:

$$F2 = \sum_{t=1}^{T} P_{\text{Grid(t)}} \times C_{\text{Grid(t)}} \tag{18}$$

$P_{Grid(t)}$ represents the active energy required by the grid and $C_{Grid(t)}$ represents the energy price of the grid in time t.

Function $F3$ shows the cost of charging and discharging the electric vehicles.

$$F3 = \sum_{t=1}^{T} \sum_{V=1}^{N_V} \begin{pmatrix} P_{Discharge(V,t)} \times C_{Discharge(V,t)} - \\ P_{Charge(V,t)} \times C_{Charge(V,t)} \end{pmatrix} \tag{19}$$

The discharge energy of the v^{th} vehicle is denoted as $P_{Discharge(V,t)}$;

The charge energy of the v^{th} vehicle is represented by $P_{Charge(V,t)}$;

The energy cost of discharging the v^{th} vehicle is denoted through $C_{Discharge(V,t)}$;

The energy cost of charging the v^{th} vehicle in time t is signified by $C_{Charge(V,t)}$.

G. CONTAMINANT FUNCTION

The reason behind using the contaminant function in this study is the existence of unsustainable resources and the energy grid. The contaminant function can be defined as:

$$\mathrm{F}^{\mathrm{Emission}} = \mathrm{F1} + \mathrm{F2} \tag{20}$$

Function $F1$ represents the total emissions with DG at a exact time ($t = 1 - T$) [15]:

$$F1 = Em^{DG} = \sum_{t=1}^{T} \sum_{DG=1}^{N_{DG}} P_{DG(DG,t)} \times E_{CO_2}^{DG,t} \times \forall t \in \{1, \ldots, T\} \quad \forall DG \in \{1, \ldots, N_{DG}\} \tag{21}$$

$\mathrm{E}_{\mathrm{CO2}}^{\mathrm{DG,t}}$ is representative of the carbon dioxide emission rate in unsustainable DGs.

Function $F2$ indicates the contaminant associated with the main energy generation units:

$$F2 = Em^{Grid} = \sum_{t=1}^{T} P_{Grid(t)} \times E_{CO_2}^{Grid,t} \tag{22}$$

$\mathrm{E}_{\mathrm{CO2}}^{\mathrm{Grid,t}}$ is representative of the average carbon dioxide emission rate in the main network.

H. PROBLEM CONSTRAINTS

The issue of multicriteria programming of dispersed productions and electric vehicles involves equal and unequal constraints of the network, electric vehicles and dispersed productions: balance of supply and demand, limits of generated energy of dispersed production units, extreme energy drawn from the energy network, the amount of energy stockpiled in an EV, the extreme quantity of charging and discharging in each period, and no simultaneous charging and discharging of electric vehicles. The mathematical relations of all the constraints used are as follows.

1) EQUALITY AND INEQUALITY CONSTRAINTS OF NETWEORK

The first constraint in the issue of intelligent distribution network programming is the equilibrium balance. This constraint represents the equality of production with utilization in an energy system whose relationship is as follows [15]:

$$\begin{aligned} P_{Grid(t)} &+ \sum_{DG=1}^{N_{DG}} P_{DG(DG,t)} + \sum_{wind=1}^{N_{wind}} P_{wind(DG,t)} \\ &+ \sum_{PV=1}^{N_{PV}} P_{PV(DG,t)} + \sum_{V=1}^{N_V} P_{Discharge(V,t)} \\ &= D_t + \sum_{V=1}^{N_V} P_{Charge(V,t)} + Loss_t \end{aligned} \tag{23}$$

The demand of the entire network in time t is represented as Dt;

The loss of the entire network in time t is represented as $Loss_t$.

Regarding relation (23) and the determined network, losses are calculated through the load distribution and relation (7). The energy of the dispersed productions and charging and discharging of vehicles are presented as:

$$\begin{aligned} P_{Grid(t)} = &- \sum_{DG=1}^{N_{DG}} P_{DG(DG,t)} - \sum_{wind=1}^{N_{wind}} P_{wind(DG,t)} \\ &- \sum_{PV=1}^{N_{PV}} P_{PV(DG,t)} - \sum_{V=1}^{N_V} P_{Discharge(V,t)} \\ &+ D_t + \sum_{V=1}^{N_V} P_{Charge(V,t)} + Loss_t \end{aligned} \tag{24}$$

In such a case, the energy of the network is measured through relation (24). In order prevent exceeding the total energy of the network, the allowable value of that technical constraint of the energy network is defined as relation (25):

$$P_{Grid(t)} \leq P_{sub}^{\max} \tag{25}$$

$P_{sub}{}^{max}$ is the maximum of the activated energy from the main post.

The energy stored in an electric vehicle at any one time is equal to the difference in the charge and discharge energy and its total energy with the initial energy stored in the battery. The constraint (equivalence constraint) in each vehicle is explicated through relation (26):

$$P_{Stored(V,t)} = P_{Stored(V,t-1)} - P_{Disch\arg e(V,t)} + P_{ch\arg e(V,t)} \tag{26}$$

The stored energy of vehicle V in time t is denoted as $P_{Stored(V,t)}$;

The number of electric vehicles is denoted as N_V.

Considering the initial state of battery balance V2G, $P_{Stored(V,1)}$ is set as entering data before performing the optimization. The extreme discharge limit per car is defined by equation (27), in order not to exceed the permitted amount of electric car charging energy [15]:

$$\begin{aligned} &P_{Disch\arg e(V,t)} \\ &\quad \leq P_{Disch\arg eLimit(V,t)} \times X_{(V,t)} \\ &\qquad \forall t \in \{1,\ldots,T\}, \quad \forall V \in \{1,\ldots,N_V\}, \ X \in \{0,1\} \end{aligned} \tag{27}$$

The constraint of discharging vehicle V in time t is denoted as $P_{DischargeLimit(V,t)}$.

The binary variable $X_{(V,t)}$ is the charging of a vehicle V. When this parameter is equal to 1, it shows charging, and when it is equal to 0, it shows that the vehicle is not charging. The maximum charging limit in each vehicle is defined by relation (28) in order not to exceed the permitted amount of EV charge:

$$\begin{aligned} &P_{Ch\arg e(V,t)} \\ &\quad \leq P_{Ch\ \arg eLimit(V,t)} \times Y_{(V,t)} \\ &\qquad \times \forall t \in \{1,\ldots,T\}, \quad \forall V \in \{1,\ldots,N_V\}, \ Y \in \{0,1\} \end{aligned} \tag{28}$$

The constraint of charging vehicle V in time t is denoted via $P_{ChargeLimit(V,t)}$. When this parameter is equal to 1 it shows charging, and when it is equal to 0, it shows that the vehicle is not charging. A vehicle V cannot simultaneously charge and discharge.

$$\begin{aligned} X_{(V,t)} + Y_{(V,t)} &\leq 1 \\ &\forall t \in \{1,\ldots,T\}, \quad \forall V \in \{1,\ldots,N_V\}, \\ &X, Y \in \{0,1\} \end{aligned} \tag{29}$$

Given relation (29) when the variable $X_{(V,t)}$ is equal to one, the variable $Y_{(V,t)}$ is definitely equal to zero. It could be inferred that the EV is in the charge mode [13].

2) EQUALITY AND INEQUALITY CONSTRAINTS OF THE DISPERSED PRODUCTION

To model the technical constraints of the dispersed resources and prevent this parameter from exceeding the specified value, relations (30) and (31) are expressed [15]:

$$P_{DG(DG,t)} \leq P_{DG}^{\max} \tag{30}$$

$$P_{DG(DG,t)} \geq P_{DG}^{\min} \tag{31}$$

The maximum authorized energy and minimum energy allowed for each DG is represented through P_{DG}^{max} and P_{DG}^{min}, respectively.

I. COST EFFECTIVE MODELLING OF THE DEMAND RESPONSE

To adopt a straightforward method for modeling the association between the price and the quantity of request for energy consumers, the linear function of demand should be resorted to, which is given in relation (32) [14], [15]:

$$D(i) = b - a \cdot P(i) \tag{32}$$

where $D(i)$ denotes the demand for electricity and $P(i)$ denotes the cost of consumed electricity. The slope of the demand function is represented via α and the width of its origin is represented by b. So, we can write:

$$E(i,i) = \frac{P(i)}{D(i)} \times \frac{\partial P(i)}{\partial D(i)} \tag{33}$$

By considering two past equation, we can write:

$$E(i,i) = \frac{-a \cdot P(i)}{-a \cdot P(i) + b} \tag{34}$$

At first, the electricity is expected to be consumed by customers with three diverse prices of $P(i)$, $P(j)$, and $P(k)$ for hours with low utilization of energy, average consumption hours and hours with the highest utilization of energy. When the price of electricity equals $P(i)$ EUR/kWh, the consumer use $D(i)$ kWh, and likewise for prices $P(j)$ and $P(k)$ EUR/kWh, the amount $D(j)$ and $D(k)$ kWh are considered to be the quantity of consumed electricity by consumers [15]. In this case, the amount paid by electricity consumers for energy consumption over a given time period time of (I) will be achieved through relation (35):

$$P(i) \cdot D(i) + P(j) \cdot D(j) + P(k) \cdot D(k) = I \tag{35}$$

Utilizing relation (32), the quantities of $P(i)$, $P(j)$ and $P(k)$ are computed through (36), (37), and (38), respectively [15]:

$$P(i) = \frac{-D(i) + a}{b} \tag{36}$$

$$P(j) = \frac{-D(j) + a}{b} \tag{37}$$

$$P(k) = \frac{-D(k) + a}{b} \tag{38}$$

By placing relations (36), (37) and (38) into relation (35), we have the following:

$$-D(i)^2 + b \cdot D(i) - (a)^2 \cdot \left(P(i)^2 + P(k)^2\right) + a \cdot b \cdot (P(j) + P(k)) - a \cdot I = 0 \tag{39}$$

By gaining $D(i)$ through relation (39) and calculating its derivative in proportion to $P(j)$ relation (40) comes in to play (40), as shown at the bottom of the next page:

With regards to the definition of cross-elasticity demand, the elasticity of the elastic demand (for the i^{th} period versus j^{th}) will be achieved via (41), as shown at the bottom of the next page:

So, 24-hour period the coefficients of self-stretch and reciprocity are a matrix that can be formulated as per (42).

The diagonal elements indicate the relative elasticity and its non-diagonal elements show the cross-elasticity. By considering the j^{th} column, it can be observed how the alteration of cost in the j^{th} period affects the cost of other periods [15].

1) MODELLING THE ONE PHASE ELASTIC ELECTRICITY DEMAND

Some energy demands are not able to change from one duration to another (like public lighting); these types of lighting can only be turned on or off.

$$\begin{bmatrix} \Delta D(1) \\ \Delta D(2) \\ \Delta D(3) \\ \vdots \\ \Delta D(24) \end{bmatrix} = \begin{bmatrix} E(1,1) & E(1,2) & \cdots & \cdots & E(1,24) \\ E(2,1) & E(2,2) & \cdots & \cdots & \cdots \\ \cdots & \cdots & E(i,i) & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ E(24,1) & \cdots & E(24,j) & \cdots & E(24,24) \end{bmatrix} \times \begin{bmatrix} \Delta P(1) \\ \Delta P(2) \\ \Delta P(3) \\ \vdots \\ \Delta P(24) \end{bmatrix} \tag{42}$$

If the consumer, based on the amount determined as a bonus and the penalty in the contract, changes its demand from $D_0(i)$ (initial amount of consumption) to $D(i)$, the alteration in demand is achieved according to (43).

$$\Delta D(i) = D(i) - D_0(i) \tag{43}$$

If the monetary unit of $A(i)$ is a premium in the i^{th} time period for each kilowatt-hour of demand reduction of the electricity consumer, the total paid premium due to participation in the DRP of $Pr(\Delta D(i))$ would be as given in relation (44) [15]:

$$Pr(\Delta D(i)) = A(i) \cdot [D(i) - D_0(i)] \tag{44}$$

Therefore, if a consumer participates in DRPs and does not obey the rules of the program, they would be fined. If the reduction in contracted demand for the i^{th} period is equal to the amount of the fine for the same period, then the total amount of the fine resulting from the increase in demand will be equal to the following:

$$Pen(\Delta D(i)) = Pen(i) \cdot \{IC - [D_0(i) - D(i)]\} \tag{45}$$

Assuming that $B(D(i))$ is equal to the consumption of electricity consumers during the i^{th} period, the consumption of $D(i)$ kilowatt-hours of electricity, the utilitarian of consumers in the i^{th} period will be given as (46) [15], [11]:

$$U = B(D(i)) - D(i) \cdot P(i) + Pr(\Delta D(i)) - Pen(\Delta D(i)) \tag{46}$$

According to the rules of class optimization in order to increase the utilitarian of electricity consumers to the greatest extent possible, the energy consumption $\partial U/\partial D(i)$ should be zero, so relation (47):

$$\frac{\partial U}{\partial D(i)} = \frac{\partial B(D(i))}{\partial D(i)} - P(i) + \frac{\partial Pr(\Delta D(i))}{\partial D(i)} - \frac{\partial Pen(\Delta D(i))}{\partial D(i)} = 0 \tag{47}$$

Solving (47) leads to (48):

$$\frac{\partial B(D(i))}{\partial D(i)} = P(i) + A(i) + Pen(i) \tag{48}$$

The commonly used utilitarian function of the consumers' electricity consumption is a quadratic function, which is shown in relation (49) [16]:

$$B(D(i)) = B_0(i) + P_0(i) \cdot [D(i) - D_0(i)] \cdot \left\{1 + \frac{D(i) - D_0(i)}{2E(i,i) \cdot D_0(i)}\right\} \tag{49}$$

In which $B_0(i)$ is the profit of the initial demand $D_0(i)$ and $E(i,i)$ the relative cost elasticity in the i^{th} period. By differentiating (47) and measuring $\partial B(D(i))/D(i)$ and substituting it into (48), we have (50):

$$P(i) + A(i) + Pen(i)\, P_0(i) \cdot \left\{1 + \frac{D(i) - D_0(i)}{2E(i,i) \cdot D_0(i)}\right\} \tag{50}$$

Thus, using relation (50), the quantity of the consumer demand in the i^{th} year is obtained as relation (51):

$$D(i) = D_0(i) \cdot \left\{1 + E(i,i) \cdot \frac{[P(i) - P_0(i) + A(i) - Pen(i)]}{P_0(i)}\right\} \tag{51}$$

2) STIMULATING THE MULTIPERIOD ELASTIC ELECTRICITY DEMAND

Some costs can be transferred from a time span with the highest utilization of energy to a time span with less consumption. According to the definition of mutual elasticity and assuming the linearity of the demand function, we have relation (52):

$$\frac{\partial D(i)}{\partial P(j)} = Constant \quad for\ i, j = 1, 2, 3, \ldots, 24 \tag{52}$$

In this case, the linear relation (53) between the price and the amount of demand will be established as follows [17]:

$$D(i) = D_0(i) + \sum_{\substack{j=1 \\ i \neq j}}^{24} E(i,j) \cdot \frac{D_0(i)}{P_0(i)} \cdot [P(i) - P_0(i)] \times i = 1, 2, 3, \ldots, 24 \tag{53}$$

If rewards and fines are also considered, the multiperiod model will be in the form of relation (54) [14]:

$$D(i) = D_0(i) \cdot \left\{ 1 + \sum_{\substack{j=1 \\ i \neq j}}^{24} E(i,j) \cdot \frac{[P(j) - P_0(j) + A(j) - Pen(j)]}{P_0(j)} \right\} \tag{54}$$

The cost-effective stimulation of the demand response is achieved by combining the modeling of demands with one period or several periods. Therefore, by merging the equations of 51 and 54, we can write:

$$D(i) = D_0(i) \cdot \left\{ \begin{array}{l} 1 + E(i,i) \cdot \frac{[P(i) - P_0(i) + A(i) - Pen(i)]}{P_0(i)} \\ + \sum_{\substack{j=1 \\ i \neq j}}^{24} E(i,j) \cdot \frac{[P(j) - P_0(j) + A(j) - Pen(j)]}{P_0(j)} \end{array} \right\} \tag{55}$$

It should be noted that in relation to the electric demand elasticity matrix, sticking to relation (56) is necessary:

$$\begin{cases} E(i,j) \leq 0 & \text{if } i = j \\ E(i,j) \geq 0 & \text{if } i \neq j \end{cases} \tag{56}$$

In this paper, an intelligent algorithm is used to plan the energy resources and electric vehicles. This has been used in solving large nonlinear problems due to the robustness of the algorithm and not being caught up in local optimizations [18], [19]. The main flowchart of proposed model is presented in Fig. 1.

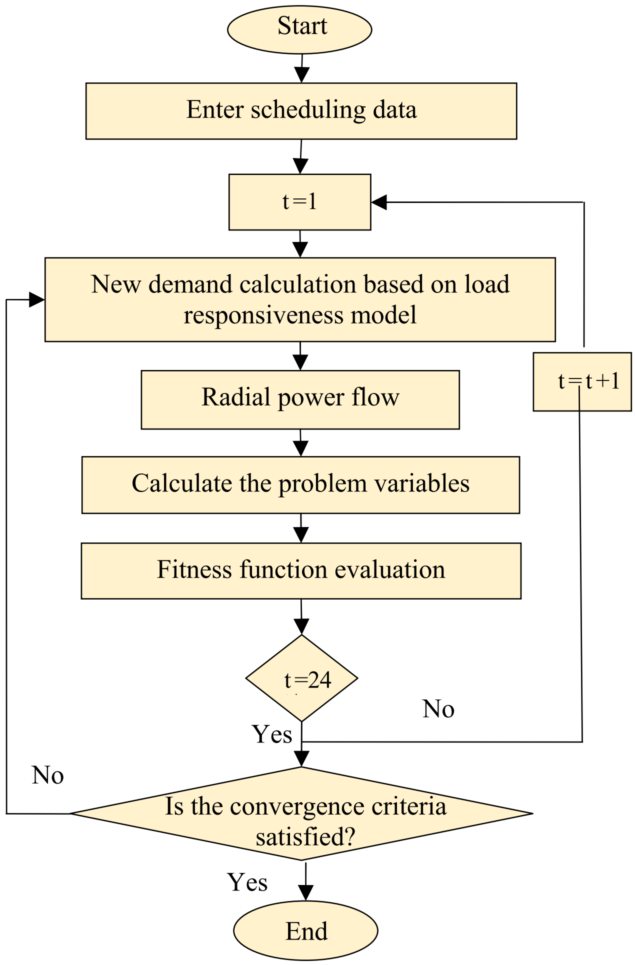

FIGURE 1. Proposed problem flowchart.

III. PROPOSED OPTIMIZATION ALGORITHM

A. CUCKOO SEARCH

The Cuckoo Search (CS) algorithm is an improved technique that can detect, produce or choose a biased search algorithm that may supply a sufficiently good solution to an optimization problem. This algorithm was advanced by Yang and Deb in 2009 [20]. CS is based on the obligate brood parasitic performance of some cuckoo species along with the Levy flight behavior of some birds and fruit flies. Lévy flight offers a contribution to smart optimization algorithms for enlarging the search range and augmenting the population variety. In this way, the algorithms are able to simply move away from local ideal solutions. Thus, it establishes an equilibrium between the global search and the local search. In the interests of simplification, the three subsequent rules are utilized in the current study: (1) every time an egg is laid by each cuckoo and

$$\frac{\partial D(i)}{\partial P(j)} = \frac{-2 \cdot a^2 \cdot P(j) + a \cdot b}{\left\{ b^2 + 4 \cdot \left[-a^2 \left(P(j)^2 + P(k)^2 \right) + a \cdot b \left(P(j) + P(k) \right) - a \cdot I \right] \right\}^{1/2}} \tag{40}$$

$$E(i,j) = \frac{-2 \cdot a^2 \cdot P(j) + a \cdot b}{\left\{ b^2 + 4 \cdot \left[-a^2 \left(P(j)^2 + P(k)^2 \right) + a \cdot b \left(P(j) + P(k) \right) - a \cdot I \right] \right\}^{1/2}} \times \frac{P(j)}{-a \cdot P(i) + b} \tag{41}$$

the process of putting eggs in nests are unsystematic; (2) the nest with the most favorable eggs or solutions is preserved for the subsequent generation; and (3) the quantity of host nets is static, and a host bird determines the egg with an assumed likelihood. When the host bird detects the unfamiliar egg, it will abandon the egg and detect another nest in another place.

B. MULTI-CRITERIA CS

CS was initially developed to deal with single-criterion optimization. Yang and Deb proposed multicriteria CS in 2013 with the aim of providing solutions for multiple objective optimization problems [21]. In fact, to provide solutions for the multicriteria optimization problems, the first and last rules are adjusted. Specifically, each K eggs would be laid by K cuckoo at a time and they are put in a host nest unsystematically. Every nest will be discarded with a specified likelihood and a novel nest with K eggs being constructed. Considering that all of the criteria must be completely regarded when assessing the excellence of the nests, non-controlled multicriteria optimal solutions should be searched. The path and location repetitive formula of the cuckoo unsystematic search nest with reference to the three rules is provided:

$$x_i^{iter+1} = x_i^{iter} + \alpha \oplus \text{Levy}(\lambda) \tag{57}$$

$$\alpha = \alpha_0(x_i^{iter} - x_{best}^{iter}) \tag{58}$$

$$\text{Levy}(\lambda) \sim \mu = t^{-\lambda}, \quad 1 < \lambda \leq 3 \tag{59}$$

In the above relations, the location of the generation is represented via x_i^{iter}. α is the stage magnitude, which is related to the scales of the proposed problem, and the coefficient is shown by 0. Entry wise multiplications are referred to by (+). Lévy λ is representative of a Lévy dispersion function that unsystematically explains the walked stages.

Arithmetically, the 3 rules can be investigated, in turn, as components of crossover, elitism, and mutation. These three components work together, by which the effectiveness of the algorithm can be evaluated [22]. Nevertheless, the Multi-Criteria Cuckoo Search (MCCS) is not without its deficiencies. Therefore, the slow merging speediness, and the low variety and constancy of the multicriteria front serve as the deficiencies of the MCCS, which restrict the application of this algorithm. Furthermore, the global search capability of MCCS is influenced by the elite selection strategy, where the result is local optima. Consequently, the aim of the current study is to suggest numerous development procedures to provide solutions for the problems and develop excellent optimization solutions.

1) POPULATION INITIALIZATION STRATEGY

Additionally, the optimization of a smart population-based meta-heuristic algorithm is widely influenced by the excellence of the primary population. The unsystematically created original solution would be of low excellence under the condition that the reasonable region is representative of a smaller expanse of the optimization range. The restraint-based population generation strategy has shown to be a practical method for providing a solution for this problem [21]. The search space would be decreased, and the excellence of the early reasonable solution would be enhanced by this strategy by limiting the first solution within a definite scope. Here, the Individual Restraints and Group Restraints (IRGR) technique are resorted to in order to progress the population initialization [21].

2) INITIAL POPULATION GENERATION WITH IRGR

In terms of policymaking problems with several steps, the decision variables at nearby steps are often highly interconnected. It can be inferred that the reasonable scope of decision variables at the present step is impacted by the values of the decision variables at the preceding step. Hence, in order to enhance the favorability of optimization, the internal restriction association of decision variables between different steps should be searched for again and the search scope should be decreased. The Individual Restraints (IR) strategy is a practical approach for ascertaining the following reasonable scope of the decision variables on the basis of their internal restraint association between the near steps and the present values of the decision variables. More to the point, all the steps of the reasonable scope of IR are computed.

C. FLOCK SEARCH APPROACH

1) FLOCK SEARCH SYSTEM

Flock trend is the behavior displayed when a bunch of birds, named a flock, are scavenging or in flight. This behavior can be simulated mathematically to emulate the flocking behaviors of birds. This model can be summarized in three main steps of; Separation, Alignment, and Cohesion. In conformity with the guidelines of the MCCS, this algorithm selects a cuckoo to discover one applicant nest each time through a Lévy flight. The MCCS would conduce poor effectiveness of population reproduction. Additionally, this method has the disadvantage of immediate confluence and is easily stuck in local optima. The flock search strategy is suggested to advance the effectiveness of the method. Notably, there is one cuckoo in each host nest that can discover one candidate nest through Lévy flight. Whereby several applicant nests can be produced by repetitions. Therefore, the performance of the flock search strategy is favorable in terms of developing the effectiveness of population reproduction and quickens the merging of the algorithm. The new location iterative mathematical definition of the cuckoo unsystematic search nest is provided:

$$x_i^{iter+1} = x^{iter} + A_1 \oplus \text{Levy}(\beta) \tag{60}$$

In the above relation, the position of the old nests and new nests produced by Lévy flight, in turn, are represented via

$$x_{new}^{iter+1} = \begin{bmatrix} x_{new}^{iter+1}(1) \\ \vdots \\ x_{new}^{iter+1}(POP) \end{bmatrix}.$$

A_1 is representative of the step size set and

$$A_1 = \begin{bmatrix} \alpha_1 \\ \vdots \\ \alpha_{POP} \end{bmatrix}.$$

$$\alpha_1 = \alpha_0 \left[x^{iter}(i) - x^{iter}_{best}(j) \right] \quad (61)$$

Subsequently, the new location of the repetitive formula of each nest is as follows:

$$x^{iter+1}_{new}(i) = x^{iter}(i) + \alpha_0 \left[x^{iter}(i) - x^{iter}_{best}(j) \right] \oplus \text{Levy}(\beta) \quad (62)$$

In the above relation, $x^{iter}_{best}(j)$ is unsystematically chosen from the uncontrolled set.

Likewise, the flock search strategy is also used when substituting the worst nests (e nests). The new sites of the replaced nests (e nests) are as follows:

$$X^{iter+1}_{replenish} = X^{iter+1}_{selecting} + A_2 \oplus \text{Levy}(\beta) \quad (63)$$

Here, $x^{iter+1}_{replenish} = \begin{bmatrix} x^{iter+1}_{replenish}(1) \\ \vdots \\ x^{iter+1}_{replenish}(\text{e}) \end{bmatrix}$ is the set of newly replaced nests. $X^{iter+1}_{selecting}$ is unsystematically chosen from the remaining nests $X^{iter+1}_{remaining}$ after removing the worst nests, which comprises e nests. $A_2 = \begin{bmatrix} \alpha'_1 \\ \vdots \\ \alpha'_e \end{bmatrix}$.

$$\alpha'_i = \alpha'_0 \left[x^{iter+1}_{selecting}(i) - x^{iter+1}_{remaining}(j) \right] \quad (64)$$

The new position of each replaced nest is found as:

$$x^{iter+1}_{replenish}(i) = x^{iter+1}_{selecting}(i) + \alpha'_0 \left[x^{iter+1}_{selecting}(i) - x^{iter+1}_{remaining}(j) \right] \oplus \text{Levy}(\beta) \quad (65)$$

In the above relation, $x^{iter+1}_{remaining}(j)$ is unsystematically chosen from the remaining nests $X^{iter+1}_{remaining}$ and $j \neq i$.

2) FAST UNCONTROLLED CLASSIFYING METHOD

Additionally, the flock search strategy is a form of mathematical population diversity. This strategy is based on the Uncontrolled Classifying Genetic Algorithm (UCGA), which is a multicriteria optimization algorithm suggested by Srinivas and Deb [22]. The favorable performance of this method in discovering a multicriteria optimal front and preserving the variety of the population is confirmed. Nevertheless, this method has the disadvantage of a high time complication for classifying, a nonselective strategy, and the impact of the distributing parameter on the multiplicity of the population. UCGA-II, which was suggested by Deb et al. [23], serves as a remedy for this problem. Most notably, an uncontrolled classifying approach is approved to decrease the computational complication. Confirming the variety is performed by adopting a choosing operator on the basis of the flocking degree and the flocking distance. Additionally, the elite strategy is presented with the aim of developing the population excellence and merging effectiveness. Currently, UCGA-II has been extensively practical for MOWSOO [24]. Additionally, this algorithm has become the yardstick for evaluating other multicriteria optimization algorithms.

In the current research, in addition to advancing the search strategy, it is reflected in the UCGA-II. First, a fast, uncontrolled classifying approach based on the elite strategy is applied to choose the new nests of host birds after merging the host nests with the recently produced candidate nests, instead of unsystematically choosing new characters in the MCCS. Like this, the Improved MCCS (IMCCS) can thoroughly benefit from the preceding excellent host bird's nests. Second, a choice operator on the basis of the flocking degree is implemented maintain variety in the population. In general, a flock search strategy that contains the flock search mechanism and fast uncontrolled classifying technique is presented for IMCCS to quicken the merging.

D. DYNAMIC ADJUSTABLE POSSIBILITY

In terms of MCCS, a fixed value serves as the possibility. Under the condition that the quantity of this value is minor, trapping the algorithm in *a P* local optima is straightforward. In the current study, the cosine declining strategy is resorted to in order to apply the dynamic adjustable alteration of the possibility. The mathematical definition is provided as follows:

$$P_a = P_{a,max} cos(\frac{\pi}{2} * \frac{T_{iter} - 1}{T_{max} - 1}) + P_{a,min} \quad (66)$$

E. TECHNIQUES OF IMCCS

In the current study, a certain development approaches in the generation of the first population and the search processes of the population are provided. First, merging the restraint alteration, IRGR is applied to develop the excellence of the first population. Then, to progress the effectiveness of the population reproduction, the flock search strategy is applied. Finally, a dynamic adjustable possibility is implemented to allow the algorithm to combine with the global best solution. The collaboration of these methods allows the IMCCS to attain quicker merging and more favorable solutions than the traditional MCCS in the proposed energy system problem. In what follows, the comprehensive phases of the IMCCS are supplied:

1) The population extent *POP*, the maximum iterations, the value range of the probability, $P_{a,max}$ and $P_{a,min}$, and the coefficient of a_0 and a'_0 are determined.

2) The constrains equations will be applied, and the first nests with IRGR are produced unsystematically.

3) The fitness of the first nests is evaluated. The uncontrolled nests are selected via using uncontrolled classifying.

4) The new applicant nests are obtained by Lévy flights.

5) The fitness values of the entire nests are computed. The old and new nests are compared.

```
Start
        Objective finction f(x)
        Generate initial population of n host nest
        Evaluate fitness and rank eggs
        While (t>MaxGeneration) or Stop criteria
            t=t+1
            Get a cuckoo randomly new solution by
            Levy flights
            Apply Flock search algorithm
            Evaluate fitness
            Choose a random nest j
            If (Fi>Fj)
                Replace j by new solution
            End if
            Worst nest is abandoned with probability Pa
            and new nest is built
            Evaluate fitness and Rank the silution and
            find current best
        End while
            Post process results and visualization
End
```

FIGURE 2. Pseudo-code of proposed optimization algorithm.

6) The uncontrolled classification is conducted, and the uncontrolled nests are selected.

7) The end of the process is when the algorithm is of the greatest quantity of repetitions. If not, part of the worst nests with a certain probability is detected and removed. Then, new replaced nests are produced. The pseudo-code of CS algorithm is presented in Fig. 2.

F. OPTIMIZATION ANALYSIS

In this section, the proposed optimization algorithm is tested on mathematical benchmark to show the validity and superiority of proposed model. Accordingly, the Langermann's function has been considered as a complex test case which is presented in Fig. 3. Obtained results of this test case is presented in Table 1. In this table, the proposed algorithm is compared with Genetic Algorithm (GA), Differential Evolution (EV), Ant Colony (ACO) and Particle Swarm Optimization (PSO). The global optimum of this function is −5.1621259 in X1=2.00299219 and X2=1.006096. The feasible region of this test case is among -2 and 12 for all parameters. Function has the following definitions:

$$f(x_1, x_2) = -\sum_{i=1}^{5} \frac{c_i \cos(\pi [(x_1 - a_i)^2 + (x_2 - b_i)^2])}{e^{\frac{(x_1-a_i)^2+(x_2-b_i)^2}{\pi}}}$$

$$a = \begin{bmatrix} 3 \\ 5 \\ 2 \\ 1 \\ 7 \end{bmatrix}, \quad b = \begin{bmatrix} 5 \\ 2 \\ 1 \\ 4 \\ 9 \end{bmatrix}, \quad c = \begin{bmatrix} 1 \\ 2 \\ 5 \\ 2 \\ 3 \end{bmatrix}, \tag{67}$$

As shown in this table, the proposed algorithm could outperform other optimization algorithms in best, average and worst values. This comparison is based on a mathematical benchmark and in the following, real world engineering test cases will be considered as comparison test case to show the validity of proposed approach.

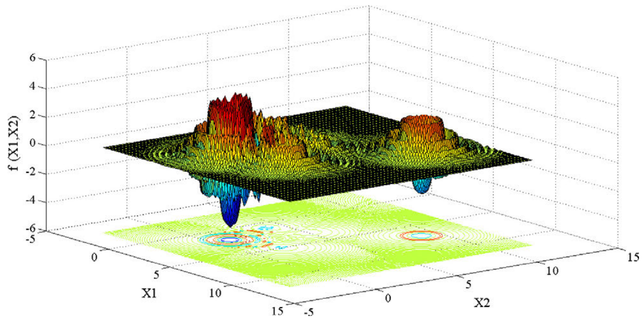

FIGURE 3. Graphical view of Langermann's function.

TABLE 1. Numerical analysis of Langermann's benchmark function through comparison with other algorithms.

Criterion	GA	DE	ACO	PSO	Proposed
Best result	-4.734	-4.803	-4.983	-5.079	-5.008
Average result	1.081	0.961	0.615	0.479	0.300
Worst result	1.974	1.765	1.437	1.339	1.001

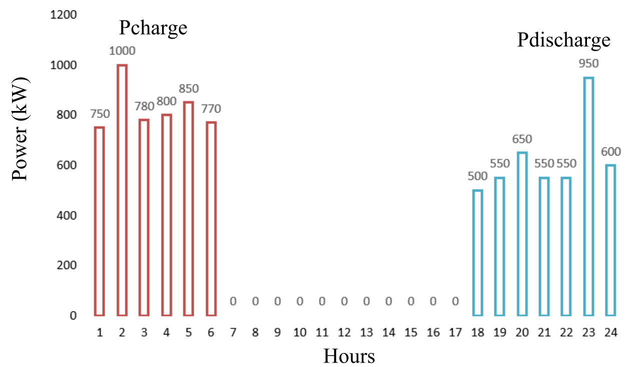

FIGURE 4. The EVs discharge and charge energy.

IV. NUMERICAL RESULTS AND ANALYSIS

This section reflects the outcomes of this study. Developing schemes for the energy resources programming problem is performed after presenting information related to the targeted networks. Providing various schemes for the programming problem of the intelligent distribution network is performed first in terms of a typical thirty-three bus network and then it is performed in terms of the actual ninety-four-bus network, which is comprised of the subsequent schemes.

A. STANDARD 33-BUS TEST CASE

A 22.6 kV thirty-three-bus distribution network serves as the practical example in this section. The DG components of this network are a photovoltaic, a wind turbine, a fuel cell and a diesel producer. A quantity of 1 is presumed for

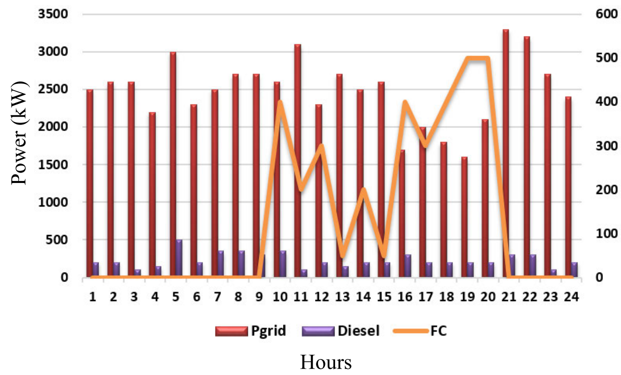

FIGURE 5. Programmed energy of the dispersed energy sources.

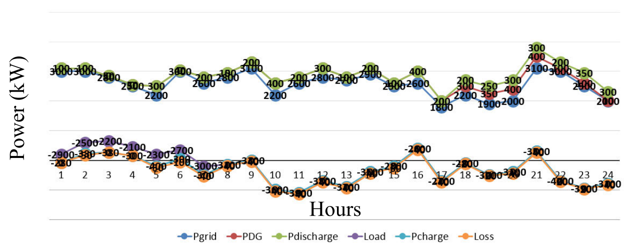

FIGURE 6. Energy stability curvature.

TABLE 2. Energy sources programming outcomes.

Networks	Process costs (€)	Losses (kW)
Traditional	7496.5	2238.42
Proposed	4179.4	2143.2

the energy factor of the dispersed productions. In this case, parallel batteries are utilized in the case of targeted electric vehicles. Within the time period of 1 to 6, the electric vehicle is charged and within the time period of 18 to 24 the electric vehicle is discharged.

1) REDUCING THE PROCESS PRICE IN THE ABSENCE OF SUSTAINABLE SOURCES

In terms of the fist scheme, the network, unsustainable dispersed productions and EVs are programmed. Here, 4 dispersed production units are resorted to (fuel cell units and diesel producers). In this phase, the programming is performed without wind and solar sustainable sources of energy. Figures 4 and 5 depict the charge and discharge of EVs and dispersed productions, respectively. The EV discharge is decreased once the price being lower. Therefore, the entire cost would be augmented. Under the condition that the price of the fuel cell is higher than the diesel generator, the fuel cell would be on for less time. The energy stability in each hour is shown in Figure 6. The outcomes of the energy sources programming are given in Table 2.

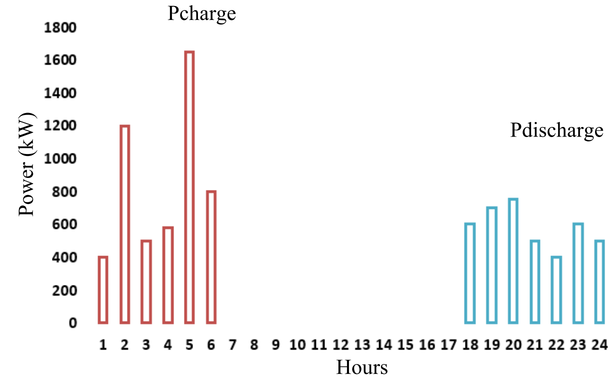

FIGURE 7. The EVs discharge and charge energy.

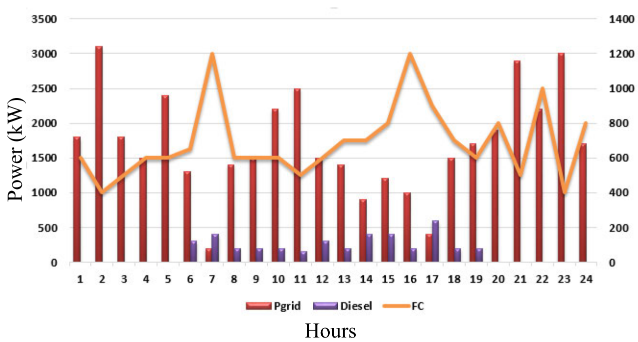

FIGURE 8. Programmed energy of the dispersed energy sources.

TABLE 3. The outcomes of energy sources programming.

Networks	Process costs (€)	Losses (kW)
Traditional	33339	2238.4
Proposed	30348	2124.5

2) DECREASING THE POLLUTION WITHOUT SUSTAINABLE SOURCES

The network, the unsustainable dispersed productions and the EVs are programmed. In this scheme there are 4 dispersed generation units (two fuel cells and two diesel producers). Throughout this phase, the programming is performed without wind or solar sustainable energy. Charging and discharging the EVs, dispersed production, and the pollution value by unsustainable productions and the energy network are the results of energy sources programming. To observe the charge and discharge energy of vehicles and to also observe the positive correlational relationship of discharging and the amount of pollution, refer to Figure 7. The dispersed productions are depicted in Figure 8. Furthermore, in this figure you could observe that a higher pollution of the diesel producer in comparison with the fuel cell would cause the diesel producer to be on for fewer hours. Figure 9 represents each hour of the energy stability curvature. In Table 3, the results of the energy sources programming are supplied. As illustrated, the pollution and losses are diminished.

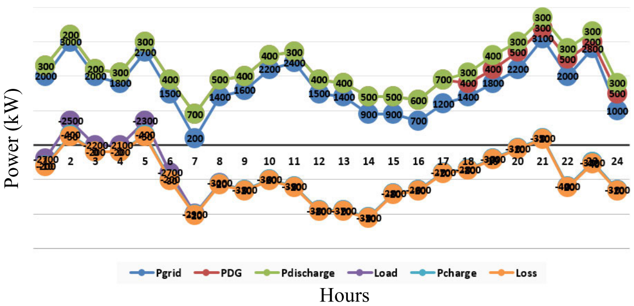

FIGURE 9. Energy stability curvature.

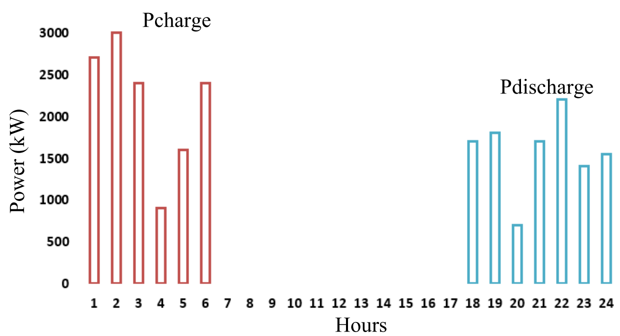

FIGURE 10. The EVs discharge and charge energy.

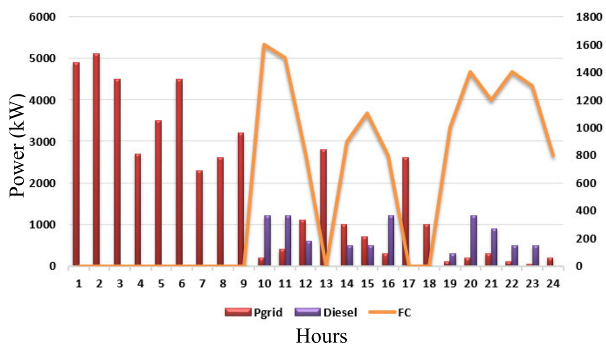

FIGURE 11. Programmed energy of the dispersed energy sources.

TABLE 4. The results of energy sources programming.

Networks	Operation costs (€)	Emission Costs (kg)
Traditional	7496.5	33338
Proposed	4508	31757

3) MULTICRITERIA OPTIMIZATION

In the case under consideration, the energy sources programming is conducted regarding the two objective functions (process cost and pollution) concurrently. Figures 10 and 11 reflect the optimal attained response from this technique and the discrete production sources programming outcomes and electric vehicles, respectively. The outputs of this multicriteria programming are represented in Table 4. Figure 12 shows the energy stability curvature for each hour.

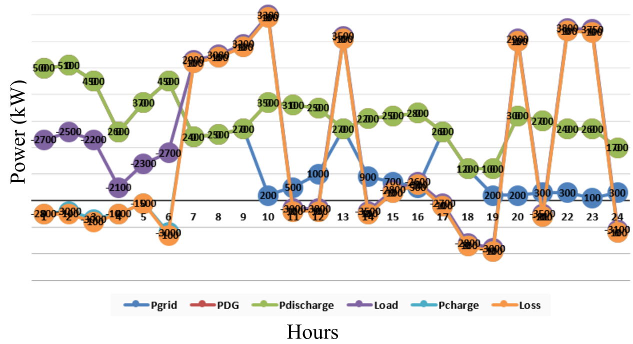

FIGURE 12. Energy stability curvature.

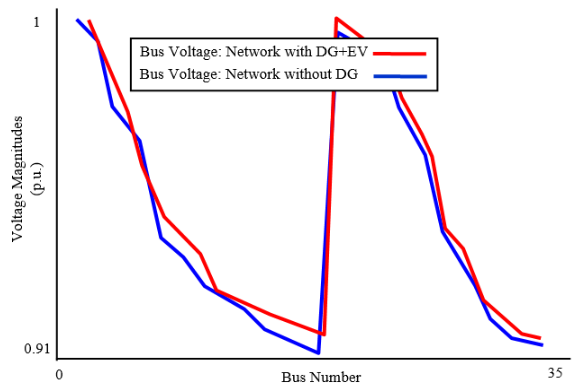

FIGURE 13. Voltage profile in the distribution network.

Figure 13 shows the potential difference in the profile development for the construction of EVs and dispersed sources to the network. Findings of this study reveal that, in terms of the connection of PEVs to the network, the charging process of vehicles is not performed at peak times, which are expensive. Therefore, the pollution would be less than other times. However, the discharging process is performed within peak hours with a high network pollution. The reasons for this selection are progressing the potential difference profile and diminishing the prices and atmosphere pollution.

B. THE PORTUGAL'S 94-BUS DISTRIBUTION NETWORK

For the second test case, the Portugal's ninety-four-bus distribution network with a potential difference of 15 kV, 53.3 MW of energy and 362.6 kw of loss is considered. Initially, the bus is assessed by disregarding the energy sources. In this assessment, the load energy of the 94-bus network is computed and substituted based on the entire plug-in load curve. The analysis of the subsequent schemes is conducted with the aim of investigating the influence of electric vehicles in diminishing the pollution and process cost.

1) DECREASING THE PROCESS COST IN THE PRESENCE OF SUSTAINABLE SOURCES OF ENERGY TO THE GREATEST EXTENT POSSIBLE

In this example, programming is conducted in terms of the main network, unsustainable dispersed productions (fuel cell and diesel producer), sustainable dispersed productions

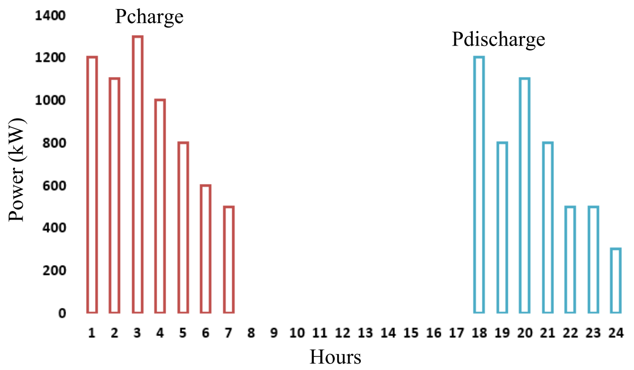

FIGURE 14. The EVs discharge and charge energy.

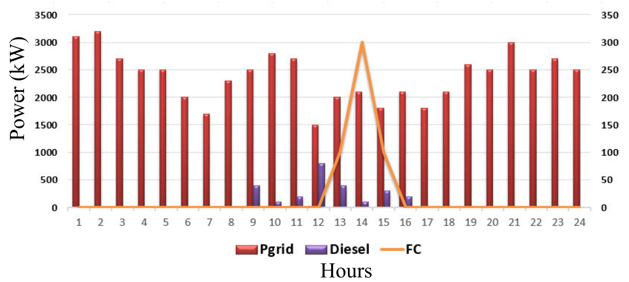

FIGURE 15. Planned energy of the dispersed energy sources.

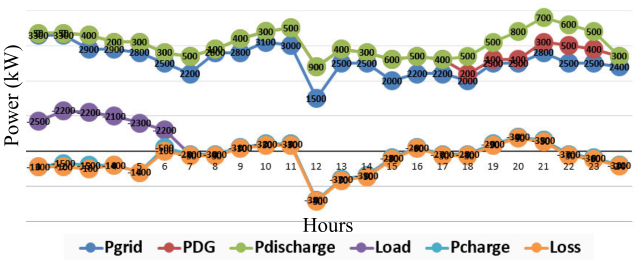

FIGURE 16. Energy stability curvature.

(wind energy plants and solar cells) and electric vehicles. This scheme is concerned with 4 dispersed production units. A single fuel cell unit, a diesel generator unit, a WT, and PV are positioned on buses 4, 21, 56, and 74, respectively. The programming is not conducted without sustainable wind and solar sources consideration. Figures 14 and 15 illustrate the programmed energy of the energy sources. It is clear that in Figure 16 that the EVs discharge is decreased under the condition that the energy price is lower. The reason behind this is that it decreases the entire cost. Furthermore, the higher price of the fuel cell compared to the diesel producer causes the fuel cell to be on for fewer hours. Likewise, using sustainable energy sources at peak times is conducive to the reduction of unsustainable dispersed sources and the process cost.

The results of the energy source planning are presented in Table 5. In this case, the uncertainty caused by renewable energy sources are also measured.

TABLE 5. Planning outcome of energy producers.

Networks	Costs of operation (€)	Emission Costs (kg)
Traditional Net.	7301.2	2804.54
Without uncertainty	3290.2	2680
With uncertainty	3189	2680

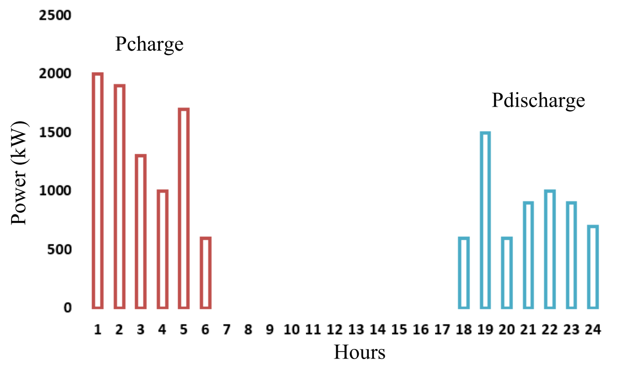

FIGURE 17. The EVs discharge and charge energy.

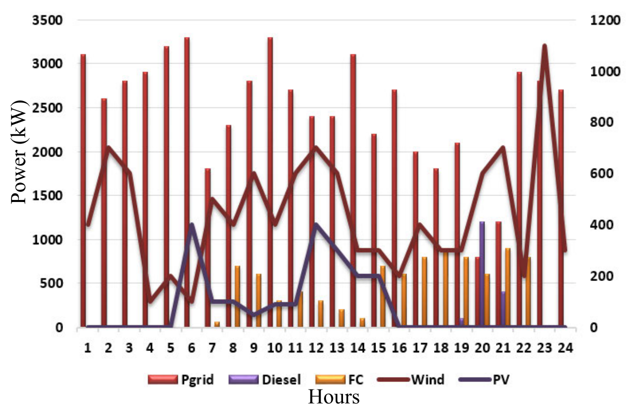

FIGURE 18. Programmed energy of the dispersed energy sources.

2) REDUCING THE POLLUTION IN THE PRESENCE OF SUSTAINABLE SOURCES TO THE GREATEST EXTENT

With respect to this instance, the programming is conducted in terms of the chief network, unsustainable dispersed productions (fuel cell and diesel generator), sustainable dispersed productions (wind turbine and solar cell) and electric vehicles. Figures 17 and 18, in turn, illustrate the energy of vehicles charging and discharging and the dispersed productions. Referring to Figure 17, it is obvious that the discharge of the vehicle is less under the condition that pollution is less. The philosophy behind this is diminishing the total pollution. Furthermore, the higher price of fuel cells compared to the diesel producer causes the fuel cell to be on for fewer hours (15). The energy stability curvature for every hour is depicted in Figure 19. The results of the energy source planning are presented in Table 6. Here, also, the impact of the solar and wind sources in terms of the uncertainty is not ignored. Resorting to sustainable energy sources has led to a

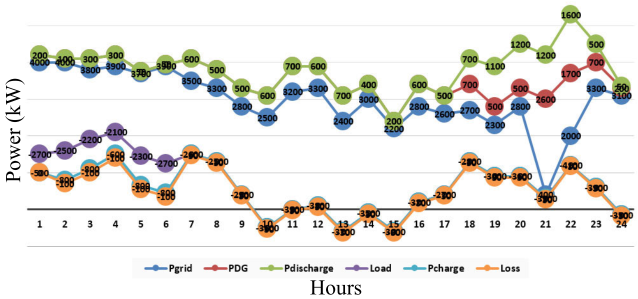

FIGURE 19. Energy stability curvature.

TABLE 6. Planning outcome of energy producers.

Grids	Operation costs (€)	Emission Costs (kg)
Classical Net.	32434	2803.45
Without uncertainty	24765	2601.12
With uncertainty	23725	2601.12

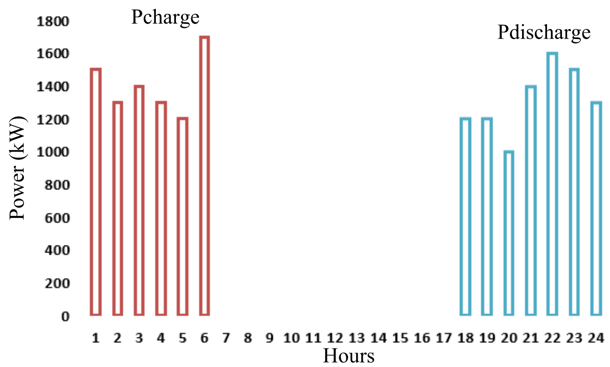

FIGURE 20. The EVs discharge and charge energy.

pollution decrease, particularly in hours with the highest load and pollution.

3) MULTICRITERIA OPTIMIZATION

Here, both the objective functions of the process price and pollution are considered when conducting the energy sources planning. The optimal response of this technique and the outputs of the dispersed producers planning and EVs under the optimal response are illustrated in Figures 20 and 21. Figure 22 reflects the outcomes of this multicriteria planning. Based on these findings, being charged during expensive hours with more pollution is not observed in terms of programming the linking EVs to the network.

Furthermore, progressing the potential difference profile and decreasing cost and environmental pollution are the benefits of discharging vehicles at peak times with more pollution. From another point of view, they are expected to deliver less energy to the network under the condition that unsustainable productions have a lower cost and pollution in the presence of sustainable energy sources. Considering that the irresolution as a result of the solar and wind sources are not ignored, the energy sources programming results are presented in Table 7.

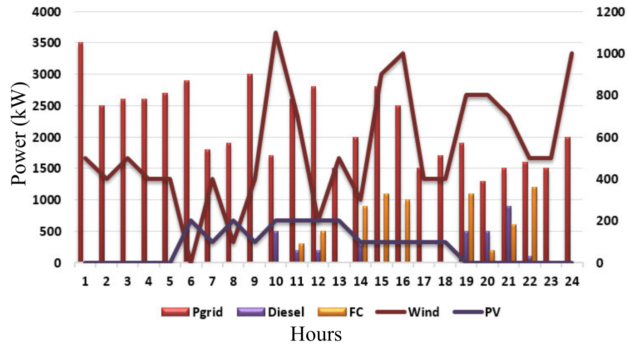

FIGURE 21. Programmed energy of the dispersed energy sources.

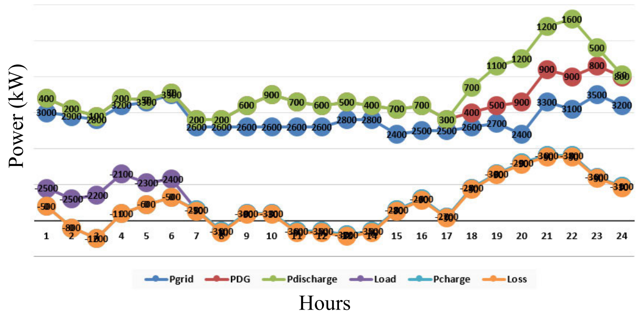

FIGURE 22. Energy stability curvature.

TABLE 7. Planning outcome of energy producers.

Grids	Operation costs (€)	Pollution costs (€)	Losses (kW)
Classical Net.	7500.3	33337	22434.54
Without demand response and uncertainty	3822	26100	1969.33
Without demand response with uncertainty	3867	26557	1969.33
With demand response without uncertainty	3267	24334	1922.14
With demand response and uncertainty	3308	25404	1922.14

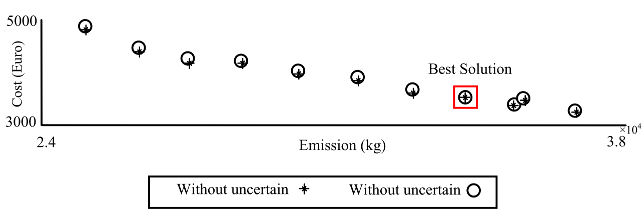

FIGURE 23. Optimum Pareto point set.

4) OPTIMUM PARETO AND CONVERGENCE GRAPH

The optimum Pareto and convergence graph of the objective functions are presented in this section. The output of the optimization in the multicriteria mode and their Pareto point curvature is shown in Figure 23. Figure 24 is a convergence trend of last analysis in the single objective mode.

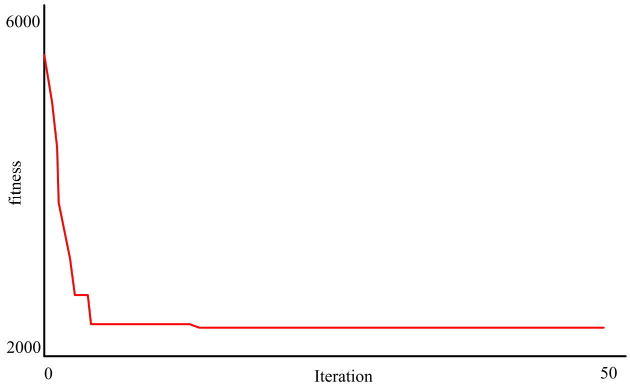

FIGURE 24. Convergence graph of the objective function in the single-objective mode.

TABLE 8. Planning outcome through different optimization algorithms for operation cost (€).

Grids	GA	PSO	Proposed
Without demand response and uncertainty	3967	3876	3822
Without demand response with uncertainty	3973	3889	3867
With demand response without uncertainty	3347	3286	3267
With demand response and uncertainty	3414	3363	3308

5) SOLUTION MODEL ANALYSIS

In this section the proposed optimization model is compared with other optimization algorithms over real world engineering test case. For this purpose, we present the Table 6 through different optimization algorithms only for operation cost. In this table (8), the proposed model is compared with GA and PSO while, obtained results proof the validity and superiority of suggested approach.

V. CONCLUSION

Meteorological and financial issues are fundamental in terms of investigating electric vehicles and sustainable sources of energy. Wirth respect to intelligent distribution systems, planning the potential of electric vehicles is crucial. Regarding the demand response schemes and electric vehicle battery storing structure, limiting the operational expenditures, calculating the intensity of the structure pollution, increasing process attempts to offer a multicriteria planning of evaluation vehicle based on the sustainable resources in an intelligent network, and removing uncertainty caused by sustainable resources and electronic vehicles serves as the contribution of this paper. In this study, a description was supplied for 33 and 94 buses, in which the energy resources scheduling is conducted. Additionally, the results of the multicriteria optimization problem of dispersed productions and electric vehicles considering the uncertainties in the presence of DRP are presented. The diagrams of the programmed energy of electric vehicles both charging and discharging, the dispersed productions and the energy stability curvature are planned for each instance. Furthermore, being charged during expensive hours with more pollution is not observed in terms of programming the linking EVs to the network. Additionally, progressing the potential difference profile and decreasing cost and environmental pollution are the benefits of discharging vehicles at peak times with more pollution. In addition to planning the outcomes of the intelligent distribution network planning problem, the responses for the objective functions and losses are computed.

Last but not least, obtained numerical results proof the validity and superiority of proposed solution model. While, the proposed algorithm could evaluate better results in comparison with PSO and GA in grids without demand response and uncertainty factors, without demand response with uncertainty facto, with demand response without uncertainty, and with demand response and uncertainty. The maximum improvement of proposed model is about 3.6 % in comparison with GA and 1.6% in comparison with PSO.

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