Energy management system for distribution networks integrating photovoltaic and storage units

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ABSTRACT

The concept of the energy management system, developed in this work, is to determine the optimal combination of energy from several generation sources and to schedule their commitment, while optimizing the cost of purchased energy, power losses and voltage drops. In order to achieve these objectives, the non-dominated sorting genetic algorithm II (NSGA-II) was modified and applied to an IEEE 33-bus test network containing 10 photovoltaic power plants and 4 battery energy storage systems placed at optimal points in the network. To evaluate the system performance, the resolution was performed under several test conditions. Optimal Pareto solutions were classified using three decision-making methods, namely analytic hierarchy process (AHP), technique for order preference by similarity to ideal solution (TOPSIS) and entropy-TOPSIS. The simulation results obtained by NSGA-II and classified using entropy-TOPSIS showed a significant and considerable reduction in terms of purchased energy cost, power losses and voltage drops while successfully meeting all constraints. In addition, the diversity of the results proved once again the robustness and effectiveness of the algorithm. A graphical interface was also developed to display all the decisions made by the algorithm, and all other information such as the states of power systems, voltage profiles, alarms, and history.

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1. INTRODUCTION

The classic electrical distribution network is made up of several equipment that require punctual management so that the network can perform its tasks without problems. Energy management is a complex task that has always been one of the main objectives of electricity grid operators. With the high demand for electricity and the increasing pollution rate caused by fossil fuel power plants, the inclusion of green energies was an efficient alternative due to the cleanliness of the energy, especially solar energy [1]. It is more and more accepted thanks to its non-harmful emissions and its cost which becomes low over the years [2]. But, with the strong penetration of these renewables into the grid, several operational challenges have been introduced. In addition to the major challenge of intermittency, which may have a negative effect on the operation of the grid, these challenges make network management more complex. With the inclusion of renewable sources and battery energy storage systems (BESS) in the network, the management task is no longer classic, it is much more complicated and requires now several other optimization, forecasting and resolution tools that are much more advanced. Due to cost variability and uncertainties associated to renewable energy sources, it is difficult to schedule the right distribution of energy between the available sources in the network at a minimum cost, in order to respond to a particular load demand at a particular time, known as economic dispatch problem. As a result, this challenging problem has become an important subject of research.

Optimal energy distribution is one of the complex and nonlinear optimization problems of power grid planning. Although there are several traditional methods to solve this problem such as mixed integer programming [3]–[5], Lagrange relaxation [6], [7], dynamic programming [8]–[11], the gradient search technique and many others, they remain limited in terms of differentiation of objective functions and manipulation of discrete variables. Meta-heuristic techniques have overcome these limitations and have demonstrated their relevance, flexibility and robustness either in terms of single-objective research or at the level of multi-objective research. Several single-objective optimization methods have been used, in the literature, to solve the energy distribution problem such as the particle swarm optimization (PSO) [12], [13], ant colony algorithms [14], genetic algorithms (GA) [15]–[17], artificial bee colony algorithms [18], [19], Cuckoo search [20], whale optimization algorithms (WOA) [21] and hybrid algorithms [22]–[25]. These methods remain limited for multi-objective optimization, which brings us directly to multi-objective techniques such as the multi-objective particle swarm optimization (MOPSO) [26], [27], the strength Pareto evolutionary algorithm (SPEA) [28], the multi-objective evolutionary algorithm (MOEA) [29], [30], the multi-objective artificial bee colony algorithm [31], and the non-dominated sorting genetic algorithm II (NSGA II) [32]–[36]. An optimization problem can be solved differently by several methods. A multi-objective algorithm can effectively solve a specific problem, and not solve others correctly. It is therefore essential to first determine the category in which the optimization problem in question fits (linear, nonlinear, convex, and non-convex). In this article, the optimization problem treated is a multi-objective, binary, nonlinear and non-differentiable problem, requiring resolution in a reasonable time. Hence the need for a binary programming model making it possible to accurately evaluate the functions to be optimized. Binary coding is the basis of genetic algorithms, because thanks to bit chains, populations can be formed. In the literature, there are several methods which have been adapted to this type of binary problem by a binary transformation such as binary MOPSO, binary whale optimization algorithm, and binary bee colony algorithm. But, it consumes computing time, which favors the use of binary algorithms directly. Genetic algorithms can be a good choice in this case.

NSGA-II is a powerful algorithm among the pioneering methods used to deal with optimization problems with nonlinear characteristics and many objectives. In most cases, NSGA-II converges to a true Pareto-optimal set and maintains a good distribution of solutions [33]. It has been widely used for various optimization problems. In the case of economic dispatch, NSGA-II has proven its robustness. Moraes *et al.* [32] have developed a new method to evaluate the impact of all exhaust gas components on the environment. They also used the non-dominated sorting genetic algorithm II for a multi-objective optimization of the distribution of the economic emission load. NSGA-II has also been used in [1] to solve economic and environmental dispatch for hybrid power systems. Rughooputh and Ah King [33] also used NSGA-II to solve the problem of environmental and economic allocation. Compared to other methods, it has been revealed that NSGA-II can identify the Pareto-optimal front with good diversity. Bora *et al.* [34] presents the learner non-dominated sorting genetic algorithm (NSGA-RL), which is an improved NSGA-II integrating a parameter-free self-tuning by reinforcement learning, for the multi-objective optimization of the environmental/economic dispatch problem (EED). A dynamic economic distribution model of the micro-grid is proposed in [35], based on a price mechanism for electricity at the time of use. Using a variant of NSGA-II, it has been proven that the precision of the solution of the multi-objective optimization model is improved, which can realize the economic distribution of the micro-grid and improve the economy. In the study [36], a model based on the elitist controlled multi-objective NSGA-II procedure is developed for the economic/emission allocation of a hybrid thermal/wind/solar production system taking into consideration the emissions of polluting gases, factors for underestimating and overestimating available energy and cost of thermal units. The results show that the algorithm is powerful in terms of cost and emission optimization with good diversity.

In the literature, several works have been carried out in order to guarantee an optimal distribution of energy in the power grid at optimal cost, or what is known as economic dispatch. Most of this work focuses on resolution techniques for optimizing the cost of produced energy and CO_2 emissions, and despite the diversity of this research, the classification of Pareto-optimal solutions is remarkably ignored. It is unfortunately almost absent in most research in the field of electrical networks. In this work, the proposed energy management system (EMS) is based on a complete and integral solution ranging from modeling to the display of optimal results, including resolution and decision-making. Great importance has also been given to the decision-making analysis. For resolution, NSGA-II was modified and used for an optimal distribution of the energy in the network in the presence of photovoltaic power plants (PV) and battery energy storage systems, while taking into consideration the intermittency of photovoltaic energy and respecting the constraints. The objective functions, in this work, take into consideration the economic aspect in terms of the injected energy cost into the network (purchased energy cost from external sources), and the operational aspect which is introduced by power losses and voltage drops. A classification of the results was made, then, by the entropy-weight based TOPSIS method compared to technique for order preference by similarity to ideal solution (TOPSIS) and analytic hierarchy process (AHP). The optimal energy distribution result can finally be displayed on an EMS interface giving the status of the network and its components and capable, also, of sending commands to the network.

This article is structured as follows: section 2 presents the mathematical formulation of the problem and the methods of resolution and classification used. An overview of the energy management system developed in this article is presented in section 3. Several tests are taken into account to validate the proposed model and are detailed in part 4. The last section is devoted to discussions and conclusion.

2. RESEARCH METHOD

2.1. The electrical distribution network and energy sources models

To model the topology of the electrical distribution network, a matrix containing the line impedances, the loads and the type of each bus is built. A power flow calculation method is then used to calculate the load distribution. In this article, it is Newton Raphson. The photovoltaic power P_{pv}, injected into the network, is a function of temperature and solar irradiance G, expressed in (1), (2):

$$P_{pv} = P_{pv,stc} \times f_{pv} \times f_{temp} \times \frac{G}{Gstc} \tag{1}$$

$$f_{tem} = 1 + \alpha_p \times (T_c - T_{c,stc}) \tag{2}$$

where $P_{pv,stc}$ is the nominal capacity of the photovoltaic generator under standard test conditions, f_{pv} is the derating factor of PV (%), f_{temp} is the temperature derating factor, G is the solar irradiance incident on the photovoltaic generator in the current time step, G_{stc} is the incident irradiance under standard test conditions (G_{stc}=1000 W/m^2), α_p is the temperature coefficient of the power (%/°C), T_c is the temperature of the PV cell in the current time step (°C), and $T_{c,stc}$ is the temperature of the PV cell under standard test conditions (25 °C).

Battery energy storage systems are modeled, in this work, to store energy from photovoltaic systems or from the electricity grid (substation) and to discharge during peak demand, when needed. The available energy in the battery energy storage system at each moment is expressed as a function of its state of charge (SoC), as in (3).

$$E_{BESS}(\mathrm{t}) = \frac{E_r \times (SoC(t) - SoCmin)}{100} \tag{3}$$

where E_r is the rated energy capacity of the BESS and SoC_{min} is its minimum state of charge (20%).

2.2. Mathematical formulation of the problem

The first step in the problem formulation is to determine the appropriate objective functions. The energy management system, proposed in this work, combines economic and operational aspects. It is designed to simultaneously optimize the three following objective functions: cost of the injected energy from the existing generation units into the network, power losses, and voltage drops, while respecting both equality and inequality constraints. The decision vector in this problem is a 19 binary element vector defined by (4).

$$X = \begin{cases} 1, \ if\ the\ energy\ source\ injects\ into\ the\ network\ or\ the\ BESS\ is\ charging \\ 0, \ if\ not \end{cases} \tag{4}$$

2.2.1. Power losses

Due to the low voltage levels, power losses are significant in distribution networks. It is therefore advantageous to minimize these losses in order to minimize the flow of current through the lines. The mathematical formulation of the active power losses is expressed by (5):

$$P_{loss} = \sum_{\substack{i=1 \\ i \neq j}}^{n} \sum_{j=1}^{n} \left(Re\left(Z_{ij}\right). \left|I_{ij}\right|^2 \right) \tag{5}$$

where P_{loss} presents the active power losses, Re (Z_{ij}) is the real part of the line impedance, i.e. the resistance between i and j, I_{ij} is the electric current transiting between i and j, and n is the number of buses.

2.2.2. Voltage drops

The energy management system must be able to generate at each time step decisions for optimal energy dispatch. So that it can stabilize the nodal voltage value close to 1 pu and improve the voltage profile. In this work, Voltage drops V_d are expressed as a function of nodal voltage V, as in (6).

$$V_d = Var(1 - V) \tag{6}$$

2.2.3. Purchased energy cost

The EMS must choose the optimal solution having a minimum cost of the purchased energy (the energy injected into the grid) from external units (PV, BESS and the upstream grid) at instant t. The purchased energy cost, used in this work, for each source in the network is shown in Table 1. For instance, the purchased energy cost from the upstream grid is supposed to be constant (average value), and only two costs were considered (off-peak and during the peak period costs). The cost function is therefore formalized in (7):

$$C_E = \sum_{i=1}^{19} UEc_i \times E_i \times X(i) \tag{7}$$

where C_E is the total energy cost, UEc is the cost of energy purchased from each energy source and E_i is the energy delivered by this source.

Table 1. Purchased energy costs

Unit	Unit injected energy cost UEc (€/MWh)
Substation (Off-peak)	43
Substation (Peak)	258
Photovoltaic system	62.5
Battery Energy Storage System	150

2.2.4. Constraints

In any optimization problem, taking into account the constraints, whether technical, economic or environmental, makes it possible to minimize the search space. In this work, the constraints to be satisfied are expressed as follows: i) the solar system can only support the loads if the value of solar irradiance G is greater than 100 W/m^2, ii) the BESS must absolutely be charged once its state of charge SoC level reaches 20%, iii) during BESS operation and in order to conserve batteries life, the SoC must stay within the appropriate limits, and iv) the voltage at each node i has to verify the inequality: 0.95 pu ≤Vi ≤1.05 pu. To manage them well, a penalty function has been developed to eliminate all solutions that do not respect the constraints.

2.3. Resolution method

As a modified version of the NSGA algorithm, the non-dominated sorting genetic algorithm NSGA-II addresses the lack of elitism and crossover parameter calibration in NSGA. In order to avoid these drawbacks, Deb *et al.* [37] have proposed NSGA-II which introduces the notion of elitism in order to keep the best parent-child individuals among the parent-child population. NSGA-II uses congestion distancing techniques for a variety of solutions and always seeks to give a solution close to the Pareto-optimal solution thanks to its non-dominated sorting technique. NSGA-II has shown better performance in terms of convergence and diversity of solutions when compared to other evolutionary algorithms.

2.4. Multicriteria decision-making techniques

Choosing the optimal solution among a set of solutions in the Pareto front is a difficult task that requires the contribution of a multicriteria decision analysis well suited to the problem. Several are the decision-making methods in the literature, namely AHP, simple additive weighting (SAW), TOPSIS [38], elimination et choice translating reality (ELECTRE), and preference ranking organization method for enrichment evaluations (PROMETHEE). These methods are differentiated by their nature of subjective weighting (direct weighting or pairwise comparison) or objective weighting (mean weighting, standard deviation, entropy). Subjective weighting is characterized by its role in determining the importance of the criteria and it is up to the decision maker to set his preferences. The decision maker does not need to intervene in the case of objective weighting because the weights are determined automatically. In this work, three classification techniques have been highlighted; AHP, TOPSIS, and entropy-TOPSIS.

2.4.1. Analytic hierarchy process

Developed by Saaty in 1980 [39], the AHP method is intended to be used for complex problems with a multi-criteria decision. It allows to examine a problem at different hierarchical levels (from a higher level to a lower level) to finally compare the pairs of criteria in a simple and logical way. Criterion weights are determined during the process after expert opinion on the importance of each criterion (using the Saaty numerical scale). Its advantage is its ability to manage different classes of quantitative and qualitative criteria. The process of this method is presented in [40].

2.4.2. Technique for order of preference by similarity to ideal solution

It is a multi-criteria decision technique which aims to classify and select the alternatives via Euclidean distance. Proposed by Yoon and Hwang in 1981 [41], TOPSIS makes it possible to choose an alternative, among several, which has the greatest distance to the ideal negative alternative (the worst alternative on all criteria) and the shortest distance to the positive ideal alternative (the best alternative on all criteria). Its advantage is the introduction of the notion of the ideal and the anti-ideal. TOPSIS can be used to sort the optimal Pareto front solutions and help the decision maker to choose among them, and this by considering them as alternatives and the objective functions as criteria. Weights are given by decision makers to represent their preferences between criteria. TOPSIS technique is detailed in [38].

2.4.3. The entropy method combined with TOPSIS

Based on Shannon's entropy, the entropy method is an objective method which, using objective information from criteria, calculates weights in an objective manner. It was proposed by Shannon (1948) in order to evaluate the information content of a certain message. In the literature, and in order to improve classification results, the entropy method has been used in combination with several methods. Huang [42] conducted an empirical study in order to demonstrate the feasibility of the entropy-TOPSIS method for real applications of information system selection. The entropy of information was used to determine the objective weights of the assessment criteria, and TOPSIS was modified and used to rank the alternatives in order of preference and then select an appropriate information system. Wang *et al*. [43] also adopted TOPSIS entropy to evaluate 22 symbiotic technologies in an industrial steel network. This hybrid method was also the choice of Kaynak *et al.* [44] in order to compare the innovation performances of four candidate countries for accession to the European Union; Serbia, Macedonia, Turkey and Iceland. Ding *et al.* [45] used an AHP-entropy approach to determine the influence factor weights of construction waste landfills. Bakhoum and Brown [46] proceeded to the combination of AHP-TOPSIS-entropy for a durable classification of structural materials. With the increasing complexity of decision-making, assigning weights to a set of criteria is paramount. Hence the need to extend classic TOPSIS to a synthetic decision system capable of meeting the demands of today's complex decision-making and objectively determining weights. In this case, the entropy method was introduced and integrated to TOPSIS.

3. THE PROPOSED ENERGY MANAGEMENT SYSTEM

The architecture of the overall network management system is shown in Figure 1. It is composed of four modules; quality management system, outage management system, energy management system and distribution management system. Each dedicated to specific functions in the network.

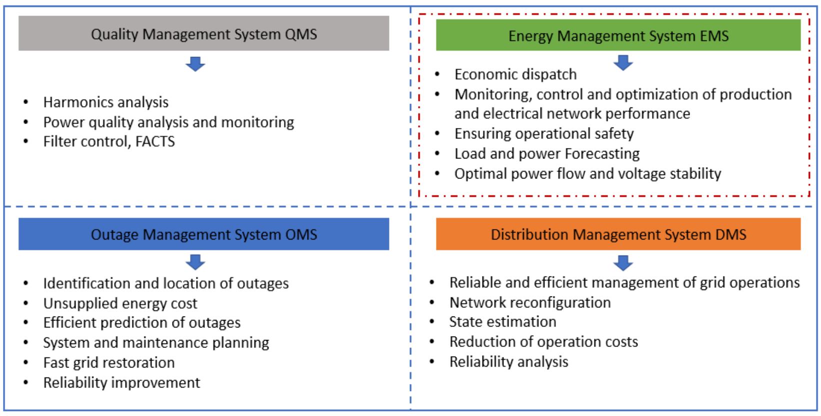

Figure 1. Architecture of the network management system

In this article, attention will be directed to the energy management system EMS (module 2). This module is made up of modeling, resolution, classification, and display sub-modules. The aim of the EMS is to generate appropriate actions for all energy sources so that energy distribution is optimized to meet demand. It must ensure short-term energy allocation planning at minimized costs depending on the load. The proposed EMS, in this article, is based on NSGA-II to solve the economic energy distribution and engagement of units. The resolution of the problem consists in determining the optimal states (0/1) of the various energy sources and deals with the optimal planning of energy injected into the network, subject to system operating constraints. Figure 2 represents the proposed energy management system inputs and outputs. Based on the data and system inputs, the EMS performs modeling, resolution using NSGA-II and classification of Pareto-optimal solutions in order to make the optimal energy distribution decision. The whole process is represented in the flowchart in Figure 3.

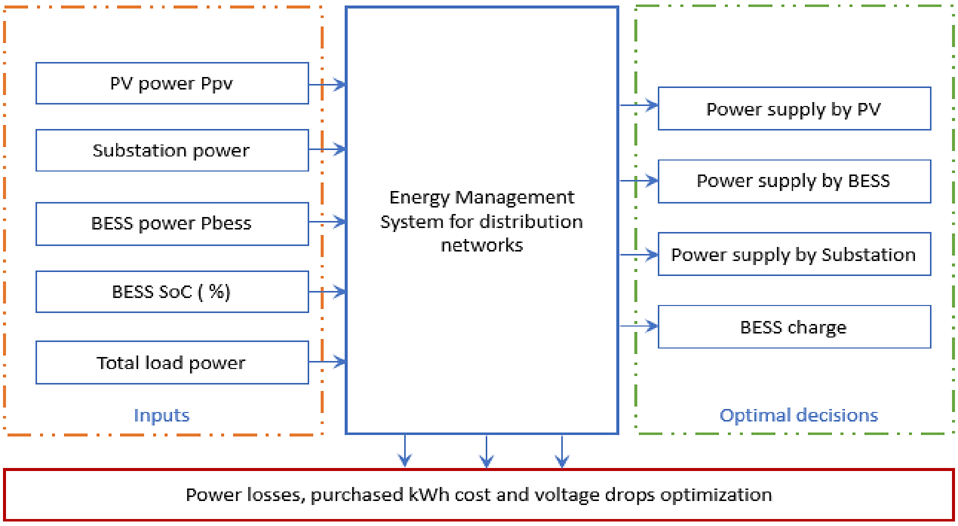

Figure 2. EMS inputs/outputs

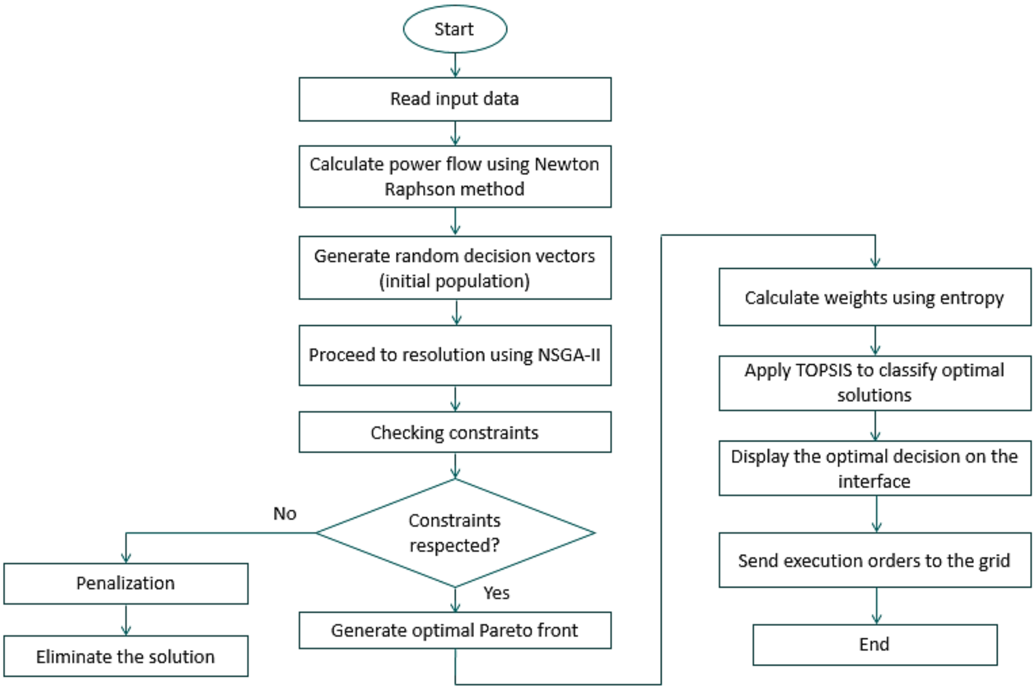

Figure 3. Global solution flowchart

4. RESULTS AND DISCUSSION

The suggested NSGA-II algorithm was tested on a modified IEEE 33 bus test network containing photovoltaic and battery systems placed at optimal locations [47]. The rated power of photovoltaic systems PV 1, 2, 3, 4, 5, 6, 7, 8, 9, 10 is 1000 kW, for each, placed respectively in buses 3, 4, 5, 8, 11, 13, 24, 25, 31, 32 and the rated power/energy of BESS 1, 2, 3, and 4 is 1527.54 kW/7637.7 kWh, for each, placed respectively in buses 5, 11, 24, 31. In this article, it is assumed that the regions where PVs exist have the same solar irradiance and the BESS state of charge ranges between 20% and 100% (depth of discharge or DoD=80%), which means that the BESS cannot deliver all its stored energy.

In order to validate and show the performance of the solution, several tests were studied under different conditions. These tests are considered in specific and non-consecutive hours. It is assumed that the BESS discharges with 1527.54 kW at each time step (20% each hour), knowing that optimal decision-making and sending orders is done every hour. For each test, the parameters of the electrical network change and consequently voltage drops and power losses are generated. Therefore, the solution seeks, at every moment, to determine the optimal energy distribution in order to optimize these losses and voltage drops, in addition to the cost of purchased energy. The test conditions are presented in Table 2 ($P_{load,std}$=3715 kW is the total load power for standard IEEE 33 bus test network). Any load power greater than 100% of $P_{load,std}$ is considered in the peak period. After their execution and classification, the results of the different tests were presented in Tables 3 and 4. Table 3 shows the energy sources chosen by the system to operate at time t.

Table 2. Test conditions

Test	G (W/m^2)	Ppv (kW)	SoC1 (%)	SoC2 (%)	SoC3 (%)	SoC4 (%)	% of $P_{load,std}$
1	20	16.25	40	40	80	60	69%
2	680	552.5	20	100	20	80	90%
3	820	666.25	100	100	100	40	105%
4	0	0	100	100	100	100	125%
5	290	235.62	80	60	80	100	110%
6	1230.7	1000	20	20	20	20	100%
7	0	0	20	20	20	20	100%

Table 3. Optimal decisions made by the algorithm

Test	AHP	TOPSIS	Entropy-TOPSIS
1	BESS 2+Substation	BESS 2+Substation	BESS 2+Substation
2	-------	PV 2, 3, 4, 5, 6, 7, 8, 9, 10 +Substation+charging BESS 1, 3	10 PV+Substation+charging BESS 1, 3
3	-------	PV 1, 5, 6, 8, 9, 10	PV 3, 5, 6, 8, 9, 10
4	BESS 2, 3, 4+Substation	BESS 2, 3, 4+Substation	BESS 2, 3, 4+Substation
5	-------	PV 1, 3, 7, 8+Substation+BESS 2, 4	PV 1, 2, 3, 7, 8+BESS 2, 4
6	PV 3, 4, 5, 6, 8, 9, 10+Substation+charging BESS 1, 2, 3, 4	10 PV+charging BESS 1, 2, 3, 4	10 PV+charging BESS 1, 2, 3, 4
7	Substation	Substation	Substation

Table 4. Optimized and classified objective functions results

	AHP			TOPSIS			Entropy-TOPSIS		
Test	P (kW)	Var (1-V)	Cost (€)	P (kW)	Var (1-V)	Cost (€)	P (kW)	Var (1-V)	Cost (€)
1	64.9	1.23e-4	273.67	64.9	1.23e-4	273.67	64.9	1.23e-4	273.67
2	-------	-------	-------	88.7	2.49e-5	372.1	84.78	2.09e-5	382.87
3	-------	-------	-------	90.7	1.34e-5	249.84	94.43	9.00e-6	249.84
4	130.13	5.28e-5	703.16	130.13	5.28e-5	703.16	130.13	5.28e-5	703.16
5	-------	-------	-------	115.39	1.73e-5	540.1	116.67	1.62e-5	531.89
6	120.76	1.86e-4	558.98	77.8	1.05e-4	625	77.8	1.05e-4	625
7	1454.2	0.006	422.48	1454.2	0.006	422.48	1454.2	0.006	422.48

For AHP, an evaluation of the results is mandatory at the start, the criteria weights must be determined according to the importance of each criterion (using the Saaty numerical scale). The weights are calculated by multiplying the weight of each criterion by the weight of each alternative with respect to each criterion. The advantage of AHP is its hierarchical architecture which makes it possible to manage several classes of quantitative and qualitative criteria and to break down a complex problem into a hierarchical structure of several levels; the results of tests 1 and 4 in Table 4 proved it. For test 6, we cannot say it is the best. The method is limited to 15 sub criteria because of the randomized index RI (as for tests 2, 3 and 5). Another drawback is the instability of the ranking of alternatives in the case of a large number of alternatives.

For TOPSIS, the weights used are 0.33 for power losses, 0.33 for voltage drops and 0.34 for energy cost. We note from Tables 3 and 4 that for many tests (tests 1, 4, 6, and 7), the two classification methods entropy-TOPSIS and TOPSIS gave the same results. It should also be noted that the entropy-TOPSIS gave better results for tests 2, 3 and 5. TOPSIS is easier to apply and introduces the notion of the ideal and anti-ideal point. But, among its disadvantages the choice of an alternative among the bad ones (in the case where all the alternatives are bad) and the subjectivity of the method. Entropy-TOPSIS fills the lack of objectivity by calculating weights by the entropy method and by using the strengths of TOPSIS for classification.

In addition to the limitation of AHP method concerning number of criteria, the calculation time of this method (0.23 seconds for test 6 for example) is greater than the calculation time of TOPSIS (0.0030 seconds for the same test) and the calculation time of entropy-TOPSIS (0.0039 seconds). This longer simulation time is due to the time devoted to the preferences of the decision maker and especially with the increase in number of criteria. TOPSIS method, in this case, turned out therefore to be more powerful than AHP, but given its limitation in subjectivity, the entropy-TOPSIS can be considered better. TOPSIS can still be used when the decision maker wants obligatory to change his preferences, i.e. the priority of one criterion over another.

In order to validate the results obtained after optimization, a random scenario (which is not proposed by EMS), is generated for each test in order to compare it to the optimal decision of the EMS (using NSGA-II and entropy-TOPSIS). It is also compared to the classic scenario where only the substation supplies the loads (for all tests). Table 5 presents the scenarios considered for comparison to the optimal solutions obtained by the energy management algorithm, and their corresponding power losses, voltage drops and purchased energy costs. It should be noted that a solution is only considered better if at least two out of three of its objective functions are better than the other solution.

Table 5. Random scenarios (without energy management)

Test	Selected units for operation	P (kW)	Var (1-V)	Cost (€)
1	BESS 3, 4	73.03	1.56e-4	458.26
2	10 PV+Substation+charging BESS 1, 3, 4	137.49	4.00e-4	448.56
3	PV 1, 2, 3, 4, 5+Substation	102.91	2.74e-4	355.13
4	BESS 4+Substation	199.65	7.1e-4	1033.1
5	PV 1, 2, 3+BESS 4+Substation	137.42	4.45e-4	751.15
6	BESS 1, 2, 3+PV 1+charging BESS 4	271.35	0.001	749.89

To better show voltage, power losses and cost reduction, the voltage profiles of the different tests have been plotted in Figure 4 and histograms representing power losses and costs for all tests have also been made, as shown in Figure 5. Analyzing Figure 4, it is remarkable that the voltage profile, for all the first 6 tests, was improved and the voltage was stabilized throughout the process, compared to other scenarios (substation and without EMS) that are not proposed by the EMS. For test 7, and given the test conditions, the algorithm will choose the only possible solution which is the substation even if this solution does not respect the voltage limits in certain nodes. It is for this reason that test 7 does not appear in Figures 4 and 5. In this case, network reconfiguration is the ideal solution to avoid the violation of voltage limits, as it is a powerful tool that helps manage the network in the event of anomalies [48], [49]. The system therefore switches directly from module 2 (EMS) to module 4 (DMS), as represented in Figure 1, in order to change the topology of the electrical network and find its optimal reconfiguration.

As shown in Figure 5, power losses and the cost of purchased energy, for all the first six tests, also decreased with considerable gains. All the selected solutions by the EMS are the optimal solutions and they are better than the results of other scenarios (without optimization). It can be concluded that the proposed algorithm makes it possible to find the optimal energy distribution, according to solar irradiance, BESS state of charge and load demand, while respecting the constraints. As a result, we can say that the proposed solution allows a good management of the energy in the presence of PV and BESS. Depending on the input parameters which are variable at each instant, the resolution algorithm used in this article is able to choose the optimal solutions, and the decision-making method chooses the best solution among the optimal ones.

Once the decision is made, it will be displayed on a graphical interface developed under Python on a machine (Intel Core i7, 8 GB, 2.7 GHz) as shown in Figure 6. This interface displays information about the electrical network, the status of PV, the status of BESS, alarms, the values of power losses and voltage drops and also plots the voltage profile. The state of the switches is modeled by the colors red (open)/green (closed)/orange (charging the batteries). In addition to displaying the status of each source (whether it injects into the network or not), these switches are at the same time modeled by push buttons which can send instructions from the system to the grid.

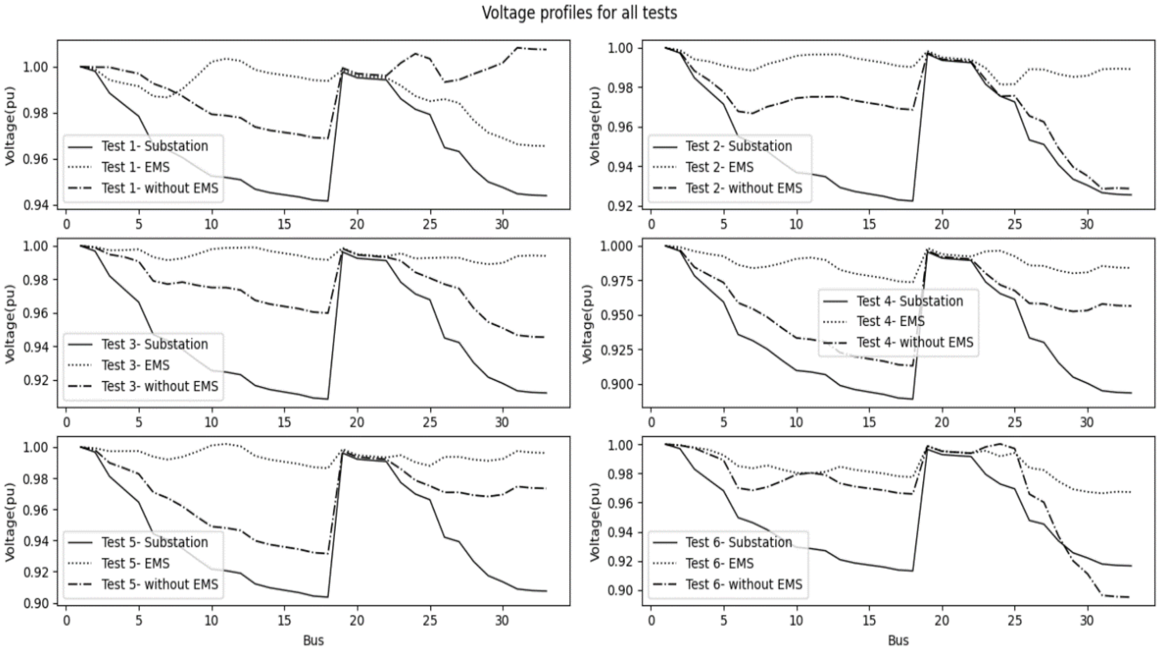

Figure 4. Voltage profiles for the different tests

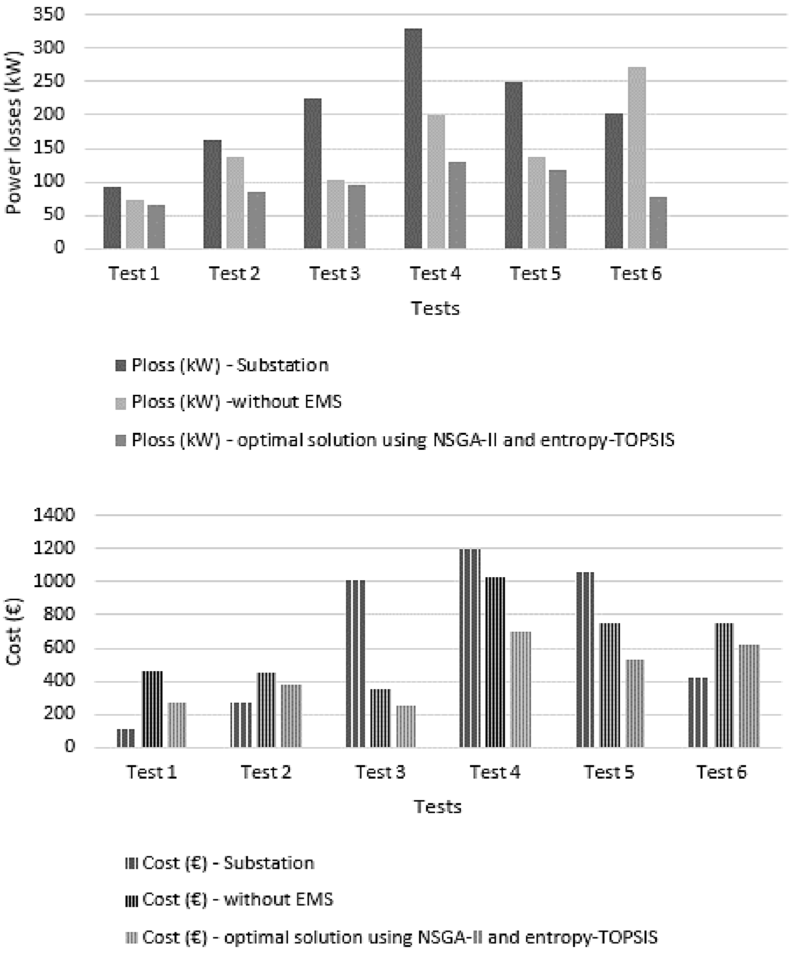

Figure 5. Power losses and purchased energy cost comparison for all scenarios

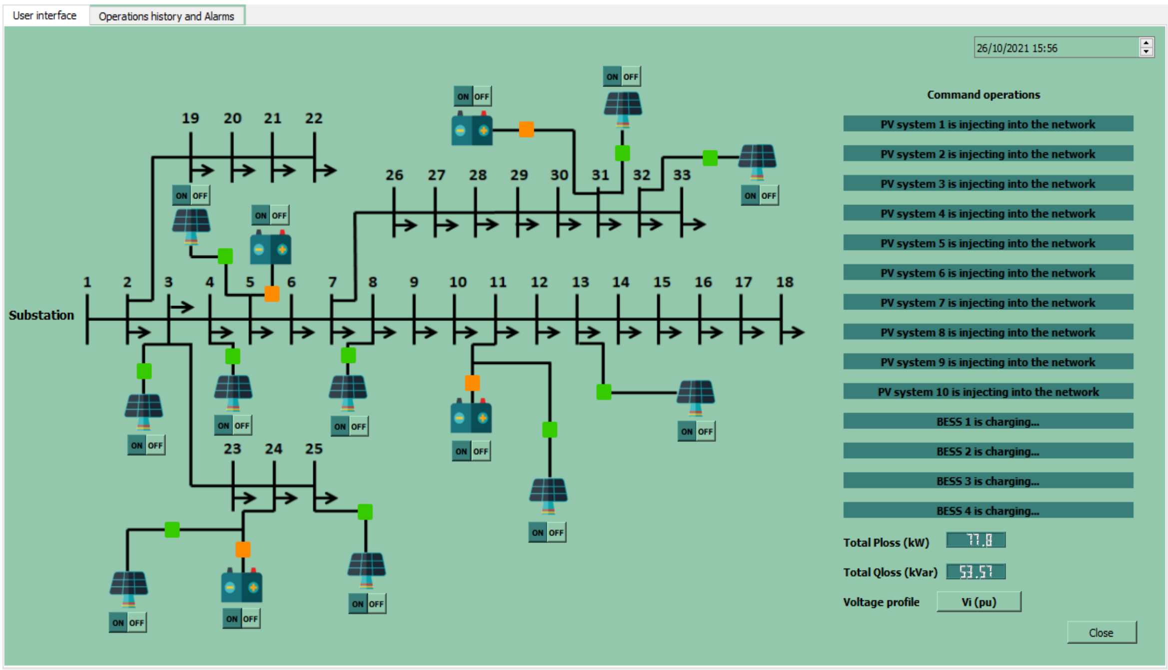

Figure 6. Graphical user interface displaying test 6

5. CONCLUSION

This article proposes an energy management system EMS, designed to determine the optimal states of production units, as well as the optimal management of these units while respecting technical or economic constraints, in order to solve the distribution energy problem and the commitment of units. The resolution was made using the NSGA-II algorithm combined with the entropy-TOPSIS classification method to find the optimal energy distribution scenario. Several tests were carried out on a modified IEEE 33 bus test network, made up of photovoltaic and battery energy storage systems to evaluate the proposed model, and the results were compared to random scenarios. The multi-objective optimization model used, in this article, has been modified to ensure diversity of results and better convergence, a penalty function has also been developed to eliminate all solutions that do not respect the constraints. A graphical interface has also been developed to display the states of the various network components (PV, BESS, switches, alarms, and voltage profile). The interface is designed to operate in both directions; from the network to the interface where all information is displayed on the user interface and from the interface to the network where the user can send orders to the network using the push buttons, e.g. send the order to cut off the injection of a BESS by opening the switch responsible for inserting this system into the network. The proposed system is an extensible system suitable to operate for any type of distribution network and with any type of energy source, in order to solve both economic and operational problems in the network. It takes into account the interests of the electrical distribution network under reasonable constraints as being a solution which does the modeling, the resolution, the classification and the display of results. It can therefore be used for optimal management of energy in distribution networks while minimizing the cost of this energy.

REFERENCES

[1] M. Basu, “Economic environmental dispatch of solar-wind-hydro-thermal power system,” *Renewable Energy Focus*, vol. 30, pp. 107–122, Sep. 2019, doi: 10.1016/j.ref.2019.04.002.

[2] C. Zedak, A. Belfqih, A. Lekbich, J. Boukherouaa, and A. Laamimi, “Implementation of an intelligent system for remote control of decentralized photovoltaic sources using the internet of things infrastructure,” in *2019 7th International Renewable and Sustainable Energy Conference (IRSEC)*, Nov. 2019, pp. 1–6, doi: 10.1109/IRSEC48032.2019.9078247.

[3] K. A. Pruitt, R. J. Braun, and A. M. Newman, “Evaluating shortfalls in mixed-integer programming approaches for the optimal design and dispatch of distributed generation systems,” *Applied Energy*, vol. 102, pp. 386–398, Feb. 2013, doi: 10.1016/j.apenergy.2012.07.030.

[4] S. Huang, W. Tang, Q. Wu, and C. Li, “Network constrained economic dispatch of integrated heat and electricity systems through mixed integer conic programming,” *Energy*, vol. 179, pp. 464–474, Jul. 2019, doi: 10.1016/j.energy.2019.05.041.

[5] N. Khan, G. Sidhu, and F. Gao, “Optimizing combined emission economic dispatch for solar integrated power systems,” *IEEE Access*, 2016, doi: 10.1109/ACCESS.2016.2587665.

[6] A. A. El-Keib, H. Ma, and J. L. Hart, “Environmentally constrained economic dispatch using the LaGrangian relaxation method,” *IEEE Transactions on Power Systems*, vol. 9, no. 4, pp. 1723–1729, Nov. 1994, doi: 10.1109/59.331423.

[7] K. S. Hindi and M. R. Ab Ghani, “Dynamic economic dispatch for large scale power systems: a Lagrangian relaxation approach,” *International Journal of Electrical Power and Energy Systems*, vol. 13, no. 1, pp. 51–56, Feb. 1991, doi: 10.1016/0142-0615(91)90018-Q.

[8] Z.-X. Liang and J. D. Glover, “A zoom feature for a dynamic programming solution to economic dispatch including transmission losses,” *IEEE Transactions on Power Systems*, vol. 7, no. 2, pp. 544–550, May 1992, doi: 10.1109/59.141757.

[9] Y. Xu, W. Zhang, and W. Liu, “Distributed dynamic programming-based approach for economic dispatch in smart grids,” *IEEE Transactions on Industrial Informatics*, vol. 11, no. 1, pp. 166–175, Feb. 2015, doi: 10.1109/TII.2014.2378691.

[10] H. Shuai, J. Fang, X. Ai, Y. Tang, J. Wen, and H. He, “Stochastic optimization of economic dispatch for microgrid based on approximate dynamic programming,” *IEEE Transactions on Smart Grid*, vol. 10, no. 3, pp. 2440–2452, May 2019, doi: 10.1109/TSG.2018.2798039.

[11] D. L. Travers and R. J. Kaye, “Dynamic dispatch by constructive dynamic programming,” *IEEE Transactions on Power Systems*, vol. 13, no. 1, pp. 72–78, Feb. 1998, doi: 10.1109/59.651616.

[12] A. Mahor, V. Prasad, and S. Rangnekar, “Economic dispatch using particle swarm optimization: A review,” *Renewable and Sustainable Energy Reviews*, vol. 13, no. 8, pp. 2134–2141, Oct. 2009, doi: 10.1016/j.rser.2009.03.007.

[13] S. R. Salkuti, “Multi-objective based economic environmental dispatch with stochastic solar-wind-thermal power system,” *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 10, no. 5, pp. 4543–4551, Oct. 2020, doi: 10.11591/ijece.v10i5.pp4543-4551.

[14] Y.-H. Hou, Y.-W. Wu, L.-J. Lu, and X.-Y. Xiong, “Generalized ant colony optimization for economic dispatch of power systems,” in *Proc. Int. Conf. on Power System Technology*, 2002, vol. 1, pp. 225–229, doi: 10.1109/ICPST.2002.1053539.

[15] A. Bakirtzis, “Genetic algorithm solution to the economic dispatch problem,” *IEE Proceedings-Generation, Transmission and Distribution*, vol. 141, no. 4, pp. 377–382, 1994, doi: 10.1049/ip-gtd:19941211.

[16] I. G. Damousis, A. G. Bakirtzis, and P. S. Dokopoulos, “Network-constrained economic dispatch using real-coded genetic algorithm,” *IEEE Transactions on Power Systems*, vol. 18, no. 1, pp. 198–205, Feb. 2003, doi: 10.1109/TPWRS.2002.807115.

[17] S. O. Orero and M. R. Irving, “Economic dispatch of generators with prohibited operating zones: a genetic algorithm approach,” *IEE Proceedings-Generation, Transmission and Distribution*, vol. 143, no. 6, pp. 529–534, 1996, doi: 10.1049/ip-gtd:19960626.

[18] D. C. Secui, “A new modified artificial bee colony algorithm for the economic dispatch problem,” *Energy Conversion and Management*, vol. 89, pp. 43–62, Jan. 2015, doi: 10.1016/j.enconman.2014.09.034.

[19] M. Basu, “Artificial bee colony optimization for multi-area economic dispatch,” *International Journal of Electrical Power and Energy Systems*, vol. 49, pp. 181–187, Jul. 2013, doi: 10.1016/j.ijepes.2013.01.004.

[20] R. Habachi, A. Boulal, A. Touil, A. Charkaoui, and A. Echchatbi, “Economic and emission dispatch using cuckoo search algorithm,” *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 9, no. 5, pp. 3384–3390, Oct. 2019, doi: 10.11591/ijece.v9i5.pp3384-3390.

[21] F. C. K. and H. Vennila, “Economic and emission dispatch using whale optimization algorithm (WOA),” *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 8, no. 3, pp. 1297–1304, 2018, doi: 10.11591/ijece.v8i3.pp1297-1304.

[22] M. Nemati, M. Braun, and S. Tenbohlen, “Optimization of unit commitment and economic dispatch in microgrids based on genetic algorithm and mixed integer linear programming,” *Applied Energy*, vol. 210, pp. 944–963, Jan. 2018, doi: 10.1016/j.apenergy.2017.07.007.

[23] Y.-Y. Hong and P.-S. Yo, “Novel genetic algorithm-based energy management in a factory power system considering uncertain photovoltaic energies,” *Applied Sciences*, vol. 7, no. 5, Apr. 2017, doi: 10.3390/app7050438.

[24] T. A. A. Victoire and A. E. Jeyakumar, “Hybrid PSO-SQP for economic dispatch with valve-point effect,” *Electric Power Systems Research*, vol. 71, no. 1, pp. 51–59, Sep. 2004, doi: 10.1016/j.epsr.2003.12.017.

[25] F. Li, R. Morgan, and D. Williams, “Hybrid genetic approaches to ramping rate constrained dynamic economic dispatch,” *Electric Power Systems Research*, vol. 43, no. 2, pp. 97–103, Nov. 1997, doi: 10.1016/S0378-7796(97)01165-6.

[26] M. A. Abido, “Multiobjective particle swarm optimization for environmental/economic dispatch problem,” *Electric Power Systems Research*, vol. 79, no. 7, pp. 1105–1113, Jul. 2009, doi: 10.1016/j.epsr.2009.02.005.

[27] G. Sen, J. Sharma, G. Goyal, and A. Singh, “A multi-objective PSO (MOPSO) algorithm for optimal active power dispatch with pollution control,” *Mathematical Modelling of Engineering Problems*, vol. 4, no. 3, pp. 113–119, Sep. 2017, doi: 10.18280/mmep.040301.

[28] M. A. Abido, “Environmental/economic power dispatch using multiobjective evolutionary algorithms,” *IEEE Transactions on Power Systems*, vol. 18, no. 4, pp. 1529–1537, Nov. 2003, doi: 10.1109/TPWRS.2003.818693.

[29] M. A. Abido, “Multiobjective evolutionary algorithms for electric power dispatch problem,” *IEEE Transactions on Evolutionary Computation*, vol. 10, no. 3, pp. 315–329, Jun. 2006, doi: 10.1109/TEVC.2005.857073.

[30] Y. Zhu, J. Wang, and B. Qu, “Multi-objective economic emission dispatch considering wind power using evolutionary algorithm based on decomposition,” *International Journal of Electrical Power and Energy Systems*, vol. 63, pp. 434–445, Dec. 2014, doi: 10.1016/j.ijepes.2014.06.027.

[31] S. K. Gachhayat, S. K. Dash, and P. Ray, “Multi objective directed bee colony optimization for economic load dispatch with enhanced power demand and valve point loading,” *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 7, no. 5, pp. 2382–2391, Oct. 2017, doi: 10.11591/ijece.v7i5.pp2382-2391.

[32] N. M. Moraes, U. H. Bezerra, J. L. Moya Rodríguez, M. H. R. Nascimento, and J. C. Leite, “A new approach to economic-emission load dispatch using NSGA II. Case study,” *International Transactions on Electrical Energy Systems*, vol. 28, no. 11, Nov. 2018, doi: 10.1002/etep.2626.

[33] H. C. S. Rughooputh and R. T. F. Ah King, “Environmental/economic dispatch of thermal units using an elitist multiobjective evolutionary algorithm,” in *IEEE Int. Conf. on Industrial Technology*, 2003, pp. 48–53, doi: 10.1109/ICIT.2003.1290230.

[34] T. C. Bora, V. C. Mariani, and L. dos S. Coelho, “Multi-objective optimization of the environmental-economic dispatch with reinforcement learning based on non-dominated sorting genetic algorithm,” *Applied Thermal Engineering*, vol. 146, pp. 688–700, Jan. 2019, doi: 10.1016/j.applthermaleng.2018.10.020.

[35] F. Zhao, J. Yuan, and N. Wang, “Dynamic economic dispatch model of microgrid containing energy storage components based on a variant of NSGA-II algorithm,” *Energies*, vol. 12, no. 5, Mar. 2019, doi: 10.3390/en12050871.

[36] A. R. Abul’Wafa, “Optimization of economic/emission load dispatch for hybrid generating systems using controlled Elitist NSGA-II,” *Electric Power Systems Research*, vol. 105, pp. 142–151, Dec. 2013, doi: 10.1016/j.epsr.2013.07.006.

[37] K. Deb, S. Agrawal, A. Pratap, and T. Meyarivan, “A fast elitist non-dominated sorting genetic algorithm for multi-objective optimization: NSGA-II,” in *International conference on parallel problem solving from nature*, vol. 1917, Berlin, Heidelberg: Springer Berlin Heidelberg, 2000, pp. 849–858.

[38] A. Lekbich, A. Belfqih, T. Ouaderhman, J. Boukherouaa, and F. El Mariami, “An analytical multicriteria model based on graph

theory for reliability enhancement in distribution electrical networks," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 9, no. 6, pp. 4625–4636, Dec. 2019, doi: 10.11591/ijece.v9i6.pp4625-4636.
[39] T. L. Saaty, *What is the analytic hierarchy process?* Springer, Berlin, Heidelberg, 1988.
[40] P. Andarani and W. Budiawan, "Multicriteria decision analysis for optimizing site selection of electronic and electricity equipment waste dismantling and sorting facility (Case study: In Indonesia, using AHP)," in *2015 International Conference on Science in Information Technology (ICSITech)*, Oct. 2015, pp. 264–269, doi: 10.1109/ICSITech.2015.7407815.
[41] C.-L. Hwang and K. Yoon, "Methods for multiple attribute decision making," in *Multiple Attribute Decision Making*, 1981, pp. 58–191.
[42] J. Huang, "Combining entropy weight and TOPSIS method for information system selection," in *2008 IEEE Conference on Cybernetics and Intelligent Systems*, Sep. 2008, pp. 1281–1284, doi: 10.1109/ICCIS.2008.4670971.
[43] Y. Wang, Z. Wen, and H. Li, "Symbiotic technology assessment in iron and steel industry based on entropy TOPSIS method," *Journal of Cleaner Production*, vol. 260, Jul. 2020, doi: 10.1016/j.jclepro.2020.120900.
[44] S. Kaynak, S. Altuntas, and T. Dereli, "Comparing the innovation performance of EU candidate countries: an entropy-based TOPSIS approach," *Economic Research-Ekonomska Istraživanja*, vol. 30, no. 1, pp. 31–54, Jan. 2017, doi: 10.1080/1331677X.2016.1265895.
[45] Z. Ding, M. Zhu, Z. Wu, Y. Fu, and X. Liu, "Combining AHP-entropy approach with GIS for construction waste landfill selection-a case study of shenzhen," *International Journal of Environmental Research and Public Health*, vol. 15, no. 10, Oct. 2018, doi: 10.3390/ijerph15102254.
[46] E. S. Bakhoum and D. C. Brown, "A hybrid approach using AHP-TOPSIS-entropy methods for sustainable ranking of structural materials," *Int. J. of Sustainable Engineering*, vol. 6, no. 3, pp. 212–224, 2013, doi: 10.1080/19397038.2012.719553.
[47] C. Zedak, "Optimal planning and management of photovoltaic sources and battery storage systems in the electricity distribution networks," *Przegląd Elektrotechniczny*, vol. 1, no. 8, pp. 97–102, Jul. 2020, doi: 10.15199/48.2020.08.19.
[48] A. Lekbich, A. Belfqih, T. Ouaderhman, J. Boukherouaa, and C. Zedak, "A remote decentralized reconfiguration strategy of smart grid using the internet of things," in *2019 4th World Conference on Complex Systems (WCCS)*, Apr. 2019, pp. 1–6, doi: 10.1109/ICoCS.2019.8930729.
[49] A. Lekbich, A. Belfqih, C. Zedak, J. Boukherouaa, and F. Elmariami, "Implementation of a decentralized real-time management system for electrical distribution networks using the internet of things in smart grids," *Bulletin of Electrical Engineering and Informatics (BEEI)*, vol. 10, no. 3, pp. 1142–1153, Jun. 2021, doi: 10.11591/eei.v10i3.2436.

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