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Research paper

A Probabilistic Framework for Active Distribution Network Optimal Energy Management Considering Correlated Uncertain Variables

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Abstract

Background and Objectives: Distributed generations (DGs) based on renewable energy, such as PV units, are becoming more prevalent in distribution networks due to technical and environmental benefits. However, the intermittency and uncertainty of these sources lead to technical and operational challenges. Energy storage application, uncertainty analysis, and network reconfiguration are apt therapies to resist these challenges.

Methods: Energy management of modern, smart, and renewable-penetrated distribution networks is tailored here considering the uncertainties correlations. Network operation costs including switching operations, the expected energy not served (EENS) index as the reliability objective, and the node voltage deviation suppression as the technical objective are mathematically modeled. Multi-objective particle swarm optimization (MOPSO) is considered as the optimization engine. Scenario generation method and Nataf transformation are used in probabilistic evaluations of the problem. Moreover, the technique for Order Preference by Similarity to the Ideal Solution (TOPSIS) is deployed to make a final balance between different objectives to yield a unified solution.

Results: To show the effectiveness of the proposed approach, the IEEE 33-node distribution network is put under extensive simulations. Different cases are simulated and interrogated to assess the performance of the proposed model.

Conclusion: For different objectives dealing with different aspects of the network, remarkable achievements are attained. In brief, the final solution shows 4.50% decrease in operation cost, 13.07% improvement in reliability index, and 18.85% reduction in voltage deviation compared to the initial conditions.

Introduction

With the reduction of fossil fuel resources and global concerns about environmental pollution caused by these resources, the trend towards distributed generation (DGs) based on renewable energy sources (RESs) has been increased [1]-[3]. The utilization of RESs has significantly contributed to positive environmental, technical and economic benefits. However, it has some challenges too. Due to the uncertainty in the power delivered by RESs to the network, the exploitation of these resources in distribution networks has faced with several challenges [4].

Solar energy based on photovoltaics (PVs), as one of the most common types of RESs, has attracted the attention of distribution network operators. These sources provide their output electrical power by receiving solar radiation. Changes in the intensity of sunlight during the day and the dependency to the generation power of these units cause changes in the generation of power in the distribution network nodes. On the other hand, the mismatch between generation and consumption would cause dumping of available energy. Under these conditions, the utilization and non-utilization of the available energy of these units lead to challenges such as voltage deviation in the nodes or an increase in costs in case of increased power losses [5].

Meanwhile of getting smart and moldering the networks, one of the available solutions to alleviate these conditions as well as balancing the share of RESs generation and the share of consumed load would be adoption of energy storage systems (ESS) alongside RESs [6]-[8]. For instance, using ESSs together with PV units provides the possibility of obtaining maximum power from these units and a more uniform output profile. With the help of ESSs, the output power of PVs can be stored until the time of need for their consumption. Balancing the power through ESS separates generation and consumption times, effectively. Alongside, by ESS deployment, the stability of the transmission and distribution network and the overall security of the energy system increases as well [9]-[11]. The operation strategy in networks with high penetration of RESs along with ESSs has changed during the past decades to overwhelm the probable problems. For example, in peak load conditions, the operator must reduce energy costs and improve energy efficiency; in other operating states, the reduction of greenhouse gases is considered. On the other hand, the positive effect of RESs and ESSs on the distribution network from a technical point of view depends on several factors and various considerations should be made.

The mentioned cases and sources of uncertainties have turned optimal energy management in distribution networks into a challenge task. Energy management is a set of methods and actions carried out in different systems to use energy correctly and maximize benefits or minimize costs without reducing the quality of services. In other words, energy management is a method to ensure the rational use of energy in a system to improve the efficiency of that system [12]. Efficient and dynamic energy management is essential in active distribution networks to function adequately. This helps to improve operating conditions regarding cost optimization and technical capabilities. It also enhances reliability indices and minimizes voltage deviations at network nodes.

As mentioned, renewable resources are aligned with uncertainties and if the effects of the uncertainties in the problem are not considered, the uncertain parameters would heavily influence the optimization goals. Here, the optimization plans might deviate from the desired goals and lead to the inefficiencies. Besides, various correlated uncertainties should be considered to provide reliable and durable solutions.

Several studies have been conducted on the optimal management of charging and discharging of EES besides RESs [13]-[15]. However, these studies have not modeled network reconfiguration capability. Meanwhile, some studies have used intelligent evolutionary optimization algorithms for optimal management of distribution networks considering reconfiguration. In reference [16], the enhanced gravitational search algorithm (GSA) is proposed to improve transient stability, reduce total operating costs, and reduce losses. In [17], a combined method using particle swarm optimization (PSO) and the Nelder-Mead simplex search algorithm is proposed to implement reconfiguration for reducing active power losses. Also, in [18], genetic algorithm (GA) is proposed for reconfiguring distribution networks by considering a variable population size. In the presented studies, the changes in daily load curve have been ignored and a predetermined period is considered. Therefore, these conditions cannot produce accurate results and provide an optimal solution for daily 24-hours scheduling of distribution networks. In [19], the objective function minimizes operation and reliability costs with Tabu search. ESSs serve multiple objectives including peak shaving, voltage regulation, and reliability enhancement. A method for optimal scheduling of active distribution networks is tailored in [20]. This method is a two-stage process that considers the uncertainty risk associated with RESs, load, electricity price, and system component failure. This study focuses on the optimal dispatching of active distribution networks with ESSs under these uncertain conditions.

Although these studies have addressed uncertainties, possible correlations between them were ignored. Few studies have paid attention to this gap. In [21], probabilistic energy management of an active distribution network is proposed which includes plug-in hybrid electric vehicles and power electronics devices like soft open point and smart transformer with an objective function of the average voltage deviation to be minimized, improving voltage stability, and maximizing daily profits. The correlation between uncertain input variables is modelled by modifying the "Hong's 2m point estimate method". Multi-objective DGs planning in distribution networks by considering correlations among uncertainties, i.e., wind speed, light intensity and load demand, is considered in [22]. Here, the objective function minimizes the annual total costs and risks.

The studies mentioned have analyzed the impact of correlation among uncertain input variables on the energy management problem. However, there are still gaps in terms of utilizing the probabilistic evaluation method that is independent of the problem's dimensions and the number of uncertain variables, as well as modelling the correlation between them. Additionally, there is a need to develop effective objective functions and consider the possible technical tools such as reconfiguration of distribution networks. The main contributions of this paper are summarized as follows:

- Providing a probabilistic framework for optimal reconfiguration of the distribution network, optimal scheduling of ESSs and optimal reactive power setting of the compensator for each period. In this view, the cost of purchasing energy from the upstream network and the switching cost is reduced, reliability is increased, and voltage deviation index (VDI) is suppressed;
- Proposing a scenario generation approach in probabilistic evaluation of the problem;
- Developing a multi-objective PSO (MOPSO) method to optimally schedule of the network and provide a set of optimal solutions based on the Pareto front concept;
- Deploying the technique for Order Preference by Similarity to the Ideal Solution (TOPSIS) for a trade-off between the objectives.

Modelling of Uncertainties and Their Correlations

They are different sources of uncertainties affecting the deterministic model results. Effective solutions should be considered for this issue. In this paper, three uncertain variables say as the load, the intensity of solar irradiance, and the price of electricity supplied by the substation are considered.

A. Uncertainty Modelling

- Active Power Load

For each time period, the samples of active power loads are generated by the Normal distribution function as (1) [23].

$$f(x) = \frac{1}{\sigma \times \sqrt{2\pi}} \times e^{\frac{-(x-\mu)^2}{2\times\sigma^2}} \tag{1}$$

where, σ and μ are the standard deviation and mean values, respectively. It should be mentioned that x denotes the related uncertain variable.

- Solar Radiation

The beta distribution function generates the solar irradiance samples for each time period as (2) [24].

$$f(R) = \frac{\Gamma(\alpha_\beta+\beta_\beta)}{\Gamma(\alpha_\beta)\Gamma(\beta_\beta)} \times R^{\alpha_\beta - 1} \times (1-R)^{\beta_\beta} \tag{2}$$

where, α_β and β_β are the parameters of the beta distribution function. It should be mentioned that the output power of *PV* units is the function of solar irradiance. Therefore, the related characteristic is considered as (3).

$$P^{PV}(R) = \begin{cases} P_r^{PV} \times \left(\frac{R^2}{R_{STD}R_C}\right) & 0 \le R < R_C \\ P_r^{PV} \times \frac{R}{R_{STD}} & R_C \le R < R_{STD} \\ P_r^{PV} & R_{STD} \le R \end{cases} \tag{3}$$

where, R denotes the solar radiation, R_C denotes the certain radiation point, R_{STD} denotes the solar radiation in the standard conditions, and P_r^{PV} denotes the power output of the PV unit.

- The Purchased Electricity Price

For each time period, the samples of the price of electricity supplied by the substation are generated by the Normal distribution function.

B. Correlation Modelling

The Nataf transformation, or the Nataf correlation transformation, is a mathematical technique to model correlated input variables in engineering and risk analysis. It is beneficial in situations where traditional methods assume that input variables are independent; but in reality, they exhibit correlations [25]. The steps to perform this method are summarized as follows:

- Correlation Matrix (R)

The first step is to characterize the correlations between the input variables. This is done by specifying a correlation matrix, denoted by R, which quantifies the pairwise correlations between the variables.

- Cholesky Decomposition

Once the correlation matrix R is defined, it is decomposed using the Cholesky decomposition method. The Cholesky decomposition factors a positive definite matrix into a product of a lower triangular matrix and its transpose. This decomposition transforms the correlated variables into a set of uncorrelated variables.

- Transformation Function

After obtaining the Cholesky decomposition, a transformation function is applied to the original correlated variables to obtain uncorrelated variables. This transformation involves multiplying the Cholesky factor with the vector of correlated variables.

- Inverse Transformation

Once the analysis is performed on the uncorrelated variables, the results need to be transformed back to the original correlated space. This is achieved by applying the inverse of the transformation function to the results obtained from the uncorrelated variables. The matrix M, as a matrix of uncertain variables of the problem, is represented by (4).

$$M = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_N \end{bmatrix} \tag{4}$$

The covariance matrix of the M is equal to (5).

$$C_M = E(MM^T) = R \tag{5}$$

In (5), R is a symmetric matrix and it can be written according to the Cholesky decomposition method to obtain the value of L, where L is the Cholesky factor of a lower triangular matrix. To construct the correlation vector M, assume that W is a vector with N dimensions of an uncertain variable whose values are independent and whose variance is equal to one. Therefore, its covariance matrix is given by (6).

$$C_W = E(WW^T) = I \tag{6}$$

Using (6), the covariance matrix M can be written by (7) and the correlation matrix M can be obtained.

$$C_M = E(MM^T) = E(LWW^T L^T) = R \tag{7}$$

Therefore, the correlation between the values of the uncertain vector M is applied.

C. Scenario Selection Method for Probabilistic Evaluation

In this approach, a large number of scenarios are generated to create a precise model of the system. However, developing more scenarios results in a higher computational burden. Therefore, it is essential to select a number of scenarios that reduces the computational burden while maintaining a good approximation of the uncertain parameters. The backward method eliminates duplicate scenarios or scenarios with minimum distance and helps to reduce the number of scenarios [26].

Problem Formulation

In active distribution operation scheduling, there are different time frames to be investigated. The most important one, which is the case of this study too, is the day-ahead operation scheduling of the network. This scheduling platform is usually in hourly basis, as the case of this study. The time frame resolution effects the system on computational burden and the accuracy of the obtained results which are the inputs for the next scheduling smaller time frames, such the hour-ahead and etc. This section discusses decision variables, objective functions, and all equal and unequal constraints of the developed model.

A. Decision Variables

The decision variables in this study include the state of normally open (NO) and normally close (NC) switches, the amount of charge and discharge of ESSs, and the amount of injected reactive power of capacitors at each operation interval. These variables are shown in (8).

$$Z = \left[Z_{SW} \;\; Z_{ESS} \;\; Z_{Cap}\right] \tag{8}$$

where, Z_{SW} is the opened switches, Z_{ESS} is the amount of charge and discharge of ESSs, and Z_{Cap} is the amount of reactive power injected by capacitors.

The switches opened in the problem can be expressed according to (9).

$$Z_{SW} = [\bar{Z}_{SW_1}, \bar{Z}_{SW_2}, \dots, \bar{Z}_{SW_{N_{SW}}}] \tag{9}$$

where, Z_{SW_i} denotes the i^{th} opened switch and N_{SW} denotes the number of opened switches. However, Z_{SW_i} is also in accordance by (10).

$$\bar{Z}_{SW_i} = \left[\bar{Z}^1_{SW_i}, \bar{Z}^2_{SW_i}, \dots, \bar{Z}^{N_T}_{SW_i}\right] \quad i\epsilon\{1,2,\dots,N_{SW}\} \tag{10}$$

where, $\bar{Z}^j_{SW_i}$ denotes the i^{th} opened switch in t^{th} time interval and N_T denotes the number of time intervals.

The charge/discharge amount of ESSs in the problem can be expressed by (11).

$$Z_{ESS} = [\bar{Z}_{ESS_1}, \bar{Z}_{ESS_2}, \dots, \bar{Z}_{ESS_{N_{ESS}}}] \tag{11}$$

where, $\bar{Z}_{ESS_i}$ is the charge/discharge amount of ith ESSs and N_{ESS} is the number of ESSs. However, the Z_{ESS_i} is also in accordance by (12).

$$\bar{Z}_{ESS_i} = \left[\bar{Z}^1_{ESS_i}, \bar{Z}^2_{ESS_i}, \dots, \bar{Z}^{N_T}_{ESS_i}\right] \quad i\epsilon\{1,2,\dots,N_{ESS}\} \tag{12}$$

where, $\bar{Z}^t_{ESS_i}$ denotes the charge/discharge amount of i^{th} ESSs in the t^{th} time period.

The amount of reactive power injected by capacitors in the problem can be expressed according to (13).

$$Z_{Cap} = [\bar{Z}_{Cap_1}, \bar{Z}_{Cap_2}, \dots, \bar{Z}_{Cap_{N_{Cap}}}] \tag{13}$$

where, $\bar{Z}_{Cap_i}$ is the amount of reactive power injected by the i^{th} capacitor and N_{Cap} is the number of capacitors. It should be mentioned that $\bar{Z}_{Cap_i}$ is denoted by (14).

$$\bar{Z}_{Cap_i} = \left[\bar{Z}^1_{Cap_i}, \bar{Z}^2_{Cap_i}, \dots, \bar{Z}^{N_T}_{Cap_i}\right] \quad i\epsilon\{1,2,\dots,N_{Cap}\} \tag{14}$$

where, $\bar{Z}^j_{Cap_i}$ denotes the amount of reactive power injected by the i^{th} capacitor in the t^{th} time period.

B. Objective Functions

This study considers the total energy cost purchased from the upstream network, switching cost, reliability index based on expected energy not served (EENS), and VDI as objective functions.

Each objective function is introduced in the following and their mathematical relations are stated. It should be noted that according to the developed probabilistic framework, the expected value of each objective function is considered and the relationships are presented accordingly.

- Overall Operation Cost

This objective function is given by (15).

$$Cost = \sum_{t=1}^{N_T}\sum_{k=1}^{K}\rho_k \times \left(\sum_{n=1}^{N_{Sub}} C^{ss}_{n,k,t} \times P^{ss}_{n,k,t}\right) + \sum_{t=1}^{N_T}\sum_{i=1}^{N_{SW}} C^{SW} \times |S^t_i - S^t_{0,i}| \tag{15}$$

where, K is the number of scenarios, ρ_k is the probability of k^{th} scenario, N_{Sub} is the number of substations, $C^{ss}_{n,k,t}$ is the price of energy from n^{th} substation, $P^{ss}_{n,k,t}$ is the amount of active power received from n^{th} substation belonging to k^{th} scenario in t^{th} time period, C^{SW} is the switching cost, and S^t_i and $S^t_{0,i}$ are the new and old state of the i^{th} key in t^{th} period, respectively.

- EENS as Reliability Index

To increase the reliability, EENS index is minimized in the developed model. The mentioned index can be expressed according to (16) [27]-[28].

$$EENS = \sum_{t=1}^{N_T}\sum_{k=1}^{K}\rho_k \times \left(\sum_{i=1}^{N_{Nodes}} P_{i,k,t} \times \left(\sum_{l\in H_i} U_l + \sum_{s\in H_i'} U_s'\right)\right) \tag{16}$$

where, N_{Nodes} denotes the number of nodes, $P_{i,k,t}$ denotes the sum of the active power generation and consumption of the i^{th} node belonging to the kth scenario in t^{th} period of the operation period, U_l denotes the amount of unavailability related to the repair time of the l^{th} branch down of the i^{th} node, U_s' denotes the unavailability related to the recovery time s of the branch forward of the i^{th} node, respectively. Also, H_i and H_i' are the sets of branches downstream and upstream of the i^{th} line, respectively. It should be noted that U_l and U_s' are expressed by (17) and (18), respectively.

$$U_l = \beta_l \times t_l \tag{17}$$

$$U_s' = \beta_s \times t_s' \tag{18}$$

where, β_l and β_s are the failure rates related to l^{th} and s^{th} branches, respectively. Also, t_l and t_s' are the average repair time of the l^{th} branch and the average recovery time of the s^{th} branch (distribution line), respectively.

- VDI

This objective function is defined based on difference between the network nodes' voltage magnitude and the distribution substation's voltage magnitude (usually assumed to be equal to 1 per unit) expressed by (19).

$$VDI = \frac{1}{N_T}\sum_{t=1}^{N_T}\sum_{k=1}^{K}\rho_k \times \left(\sum_{i=1}^{N_{Nodes}}(1-|V_i|)^2\right)_{k,t} \tag{19}$$

where, $|V_i|$ denotes the voltage magnitude of i^{th} node.

C. Equal and Unequal Constraints

At each time interval, the constraints related to the proposed optimization problem are considered as follows. In the probabilistic environment, the value of network output variables, such as the magnitude of the node voltage or current in distribution lines, is replaced by the expected value of these variables [29]-[30].

$$P^{ss} + \sum_{i=1}^{N_{PV}} P_{PV_i} + \sum_{i=1}^{N_{ESS}} \pm P_{ESS_i} = \sum_{i=1}^{N_{Load}} P_{L_i} + \sum_{i=1}^{N_{Lines}} P_{Losses_i} \tag{20}$$

$$Q^{ss} + \sum_{i=1}^{N_{PV}} Q_{PV_i} + \sum_{i=1}^{N_{Cap}} Q_{Cap_i} = \sum_{i=1}^{N_{Load}} Q_{L_i} + \sum_{i=1}^{N_{Lines}} Q_{Losses_i} \tag{21}$$

$$E_{i,t} = E_{i,t-1} \pm P_{ESS_i} \times \Delta t \tag{22}$$

$$E_{ESS}^{min} \le E_{ESS_i} \le E_{ESS}^{max} \qquad i \in N_{ESS} \tag{23}$$

$$-P_{ESS}^{max} \le P_{ESS_i} \le +P_{ESS}^{max} \qquad i \in N_{ESS} \tag{24}$$

$$0 \le Q_{Cap_i} \le Q_{Cap}^{max} \qquad i \in N_{Cap} \tag{25}$$

$$|V|^{min} \le \mathrm{E}[|V_i|] \le |V|^{max} \qquad i \in N_{Nodes} \tag{26}$$

$$0.9 \le |V_i| \le 1.1 \qquad i \in N_{Nodes} \tag{27}$$

$$\mathrm{P}(|V_i| \ge |V|^{max}) \le 0.05 \qquad i \in N_{Nodes} \tag{28}$$

$$\mathrm{P}(|V_i| \le |V|^{min}) \le 0.05 \qquad i \in N_{Nodes} \tag{29}$$

$$\mathrm{E}[|I_i|] \le |I_{rate_i}| \qquad i \in N_{Lines} \tag{30}$$

$$|I_i| \le 1.25 \times |I_{rate_i}| \qquad i \in N_{Lines} \tag{31}$$

$$\mathrm{P}(|I_i| \ge |I_{rate_i}|) \le 0.05 \qquad i \in N_{Lines} \tag{32}$$

where, P^{ss} and Q^{ss} are the active and reactive power received from the upstream network, respectively, N_{PV} is the number of PV units, P_{PV_i} and Q_{PV_i} are the output active and reactive power of i^{th} PV, respectively, Q_{Cap_i} is the amount of reactive power injected by i^{th} capacitor, P_{ESS_i} is the amount of charging power (with a negative sign) or the amount of discharging power (with a positive sign) corresponding to the i^{th} ESS, N_{Load} is the load number, P_{Losses_i} and Q_{Losses_i} are the active and reactive power losses of the i^{th} line, respectively, Δt is the time frame from operation period, E_{ESS_i} is the amount of energy of the i^{th} ESS, $E_{i,t}$ and $E_{i,t-1}$ are the amount of energy available in the i^{th} ESS in the t^{th} and *t-1*th time periods, respectively, E_{ESS}^{min} and E_{ESS}^{max} are the lower and upper limits of the amount of energy available in ESSs, respectively. ESS is a device which provides a solution for energy storing and then discharging. In this way, to manage the uncertainties and especially when there are fluctuations in energy generation such as wind and photovoltaics and also energy consumption such as consumer behaviors, ESS provides a place where the energy shortfall could be compensated or extra energy generation could be stored. In this way, the developed operation scheduling model should determine the energy charging/discharging of ESS beside the other decision variables. P_{ESS}^{max} is the maximum active power that can be charged and discharged by ESSs, Q_{Cap}^{max} is the maximum reactive power injected by the i^{th} capacitor, $|V|^{min}$ and $|V|^{max}$ are the lower and the upper limits of the nodes voltage magnitude, respectively. In operation scheduling problems, maintaining a proper voltage quality is of great importance for a proper service provision for customers. To do so, technical constraints are considered which keep the voltage within the operation standards in the developed model. In this study, this requirement is met by constraints (26)-(29). $P(\,)$ is the probability operator, $E[\,]$ is the expected value operator, and $|I_{rate_i}|$ is the maximum rate of i^{th} line.

Simulation Results

A. Case Study

In order to show the effectiveness of the proposed method, the IEEE 33-node test network is used. This network has 33 nodes, 32 branches, and 5 tie lines. The nominal voltage of this network is 12.66 kV [22].

It should be noted that the failure rate of the lines is considered such that the line with the lowest and highest impedance has a failure rate of 0.1 and 0.4 per year, respectively. The failure rate of the rest of the lines is obtained from the interpolation method [23]. Fig. 1 shows the single-line diagram of the IEEE standard 33-node network.

B. Assumptions

The load curve for the study case is shown in Fig. 2. It is reminded that the operation period in this study contains 24 hours by 3-hours-duration step intervals. Fig. 3 also shows the curve of variations in the purchase price of energy from the upstream network for each time period of the study period.

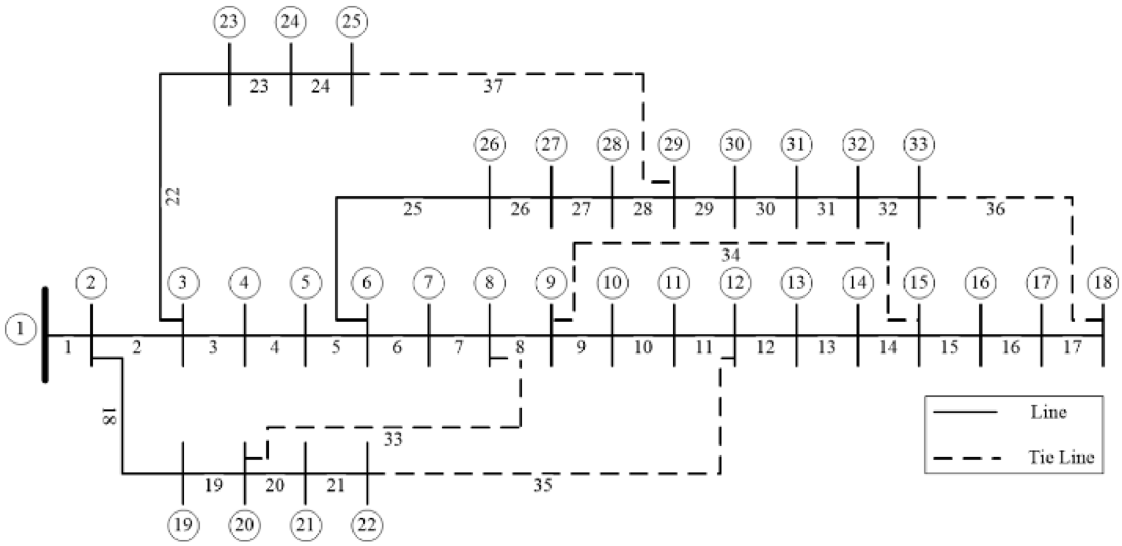

Fig. 1: The IEEE 33-node test network.

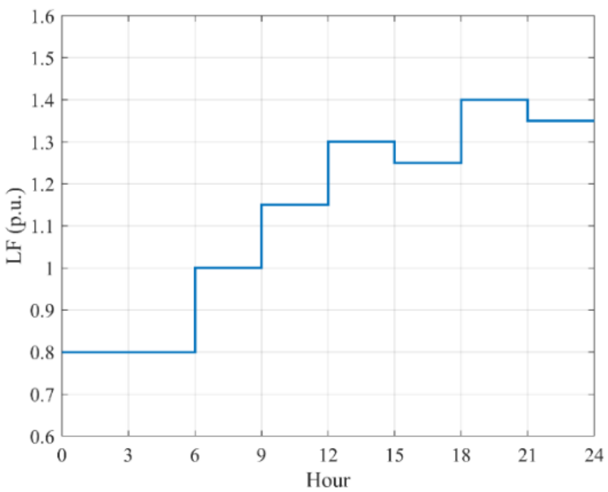

Fig. 2: Load variations curve.

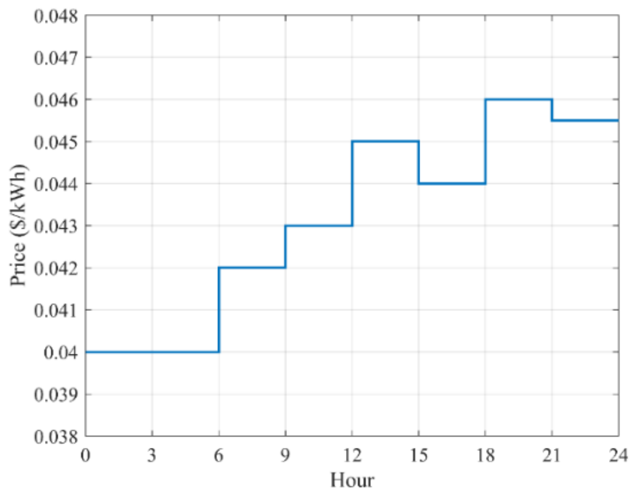

Fig. 3: Electricity price variations.

It should be mentioned that the correlation between uncertain input variables is modeled by Nataf Transformation method. For this purpose, the correlation coefficient between loads in different nodes is assumed to be 0.2, the correlation coefficient between the intensity of sunlight in different nodes is 0.7, and the correlation coefficient between energy consumption and the intensity of sunlight in the corresponding nodes is assumed to be -0.2. The charging and discharging of ESSs is assumed to be between 20% and 80% of their total capacity. For the equal or unequal constraints, the following assumptions are also considered:

$E_{ESS}^{min} = 60\ kWh$

$E_{ESS}^{max} = 240\ kWh$

$P_{ESS}^{max} = 30\ kW$

$|V|^{min} = 0.95$

$|V|^{max} = 1.05$

Also, it is assumed that three PV units with nominal capacity equal to 500 kW, 300 kW, and 400 kW are installed at nodes 8, 12, 28, respectively. It should be mentioned that the power factor of these units is considered equal to 1.

In Table 1, shape parameters of the beta distribution function in different time periods is presented. It should be noted that these parameters are used for all three PV units. For example, the probability distribution function related to the intensity of sunlight in fourth and sixth periods is presented in Fig. 4.

Table 1: Shape parameters of the beta distribution function

Period	$\alpha_\beta\ (\frac{kW}{m^2})$	$\beta_\beta\ (\frac{kW}{m^2})$
1	0	0
2	0	0
3	2.1440	0.4440
4	2.1440	0.4440
5	1.0820	0.3860
6	1.0820	0.3860
7	0.0714	0.6040
8	0	0

C. Simulation results

Table. 2 presents the statistical information related to the objective functions considered in this study in the initial evaluation conditions. These values are used to show the effectiveness of the proposed solution. It should be noted that Monte Carlo simulation (MCS) scenario generation is used to extract the information in Table 2.

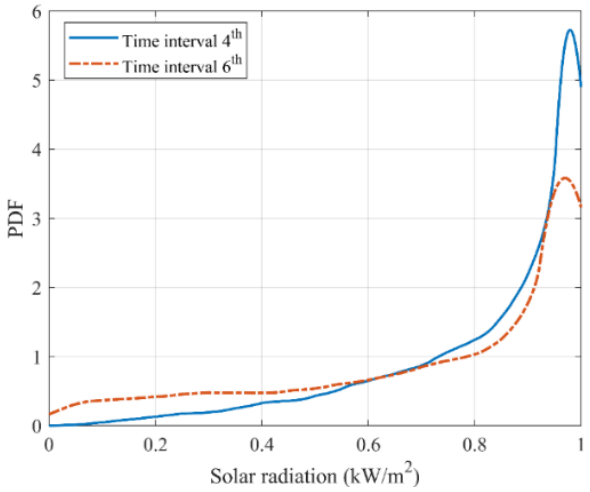

Fig. 4: Probable distribution related to the intensity of sunlight in the 4th and 6th periods.

Table 2: The values of the objective functions in the initial evaluation conditions

Objective functions	**Probabilistic methods**			
	MCS		**Scenario generation**	
	E[ ]	**σ[ ]**	**E[ ]**	**σ[ ]**
$\boldsymbol{Cost}$ ($)	4143.58	396.81	4146.87	206.89
$\boldsymbol{EENS}\ (\frac{\mathbf{kWh}}{\mathbf{year}})$	1027768	54088.96	1024829	41245.35
$\boldsymbol{VDI}\ (\boldsymbol{p.u.})$	0.1278	0.0209	0.1289	0.0127
$\boldsymbol{Time}\ (\boldsymbol{s})$	1300.12		3.45	

As it is clear from Table 2, scenario generation method has good accuracy in extracting the expected value of the objective functions; this is while, its computational time is much less than the MCS method. It is essential to mention that the standard deviation value error of the scenario generation method is higher than the expected value error of the MCS method. For example, the error of the scenario generation method compared to the MCS method in calculating the expected value and standard deviation of cost is 0.0793% and 47.86%, respectively. Since the expected value of the objective functions is used in this study, the scenario generation performance is very suitable.

The MOPSO method is used to solve the proposed problem and the TOPSIS is contemplated to establish a logical compromise between different objective functions to reach to the final solution. Table 3 shows the value of the objective functions for this set of obtained solutions. As can be seen from this table, the value of the objective functions is obtained for each solution. Among the obtained solutions, solution number 1 is the best solution from the cost point of view. Under these conditions, the value of this objective function is decreased from \$4146.87 in the initial conditions to \$3718.82. Meanwhile, solution number 15 is the best solution from the viewpoint of EENS index. This solution has achieved 19.48% improvement in this objective function.

Table 3: The value of the objective functions for the set of optimal solutions obtained based on the Pareto front using MOPSO algorithm

Solution No.	$Cost$ (\$)	$EENS\ (\frac{kWh}{year})$	$VDI\ (p.u.)$
1	3718.82	945710	0.1045
2	3774.89	930216	0.1013
3	3793.68	925520	0.1026
4	3865.81	907274	0.1019
5	3919.62	893886	0.1049
6	3960.12	890841	0.1046
7	3962.17	888589	0.1075
8	4046.62	869990	0.1068
9	4073.78	861792	0.1065
10	4128.61	851891	0.1086
11	4155.60	843368	0.1120
12	4219.15	832810	0.1136
13	4222.10	829960	0.1152
14	4247.13	825250	0.1174
15	4250.20	825160	0.1170

Also, solution number 2 is known as the best solution from the VDI point of view. By applying this solution, the value of this objective function decreases from 0.1289 to 0.1013. Fig. 5 also shows the three-dimensional compromise space between different objective functions obtained for the problem per set of optimal solutions based on the Pareto front.

The mentioned solutions are the best from the point of view of each objective function. The situation of an objective function for the best solution from the point of view of another objective function may be even worse than the initial conditions (for example, solution number 15 has worsened the value of cost compared to the first evaluation). In this regard, TOPSIS is used to choose an optimal solution that can make a compromise between all the objective functions and improve all these functions to an appropriate extent. The ranking results of this method for the set of optimal solutions are obtained in Table 3 are presented in Table 4.

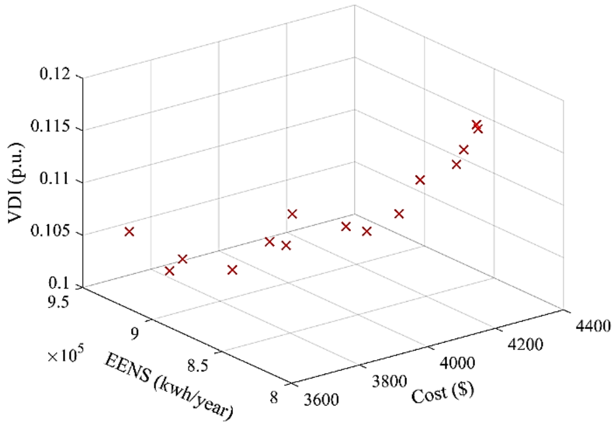

Fig. 5: Three-dimensional compromise space between the objective functions based on the set of optimal solutions obtained from the Pareto front.

Table 4: Decision-making results with TOPSIS

Scenario 1			Scenario 2		
$\omega_1 = 0.5, \omega_2 = 0.25, \omega_3 = 0.25$			$\omega_1 = 0.34, \omega_2 = 0.33, \omega_3 = 0.33$		
Rank	Solution No.	CI^+	Rank	Solution No.	CI^+
1	2	0.6967	**1**	6	0.6190
2	3	0.6210	**2**	4	0.6000
3	1	0.6786	**3**	5	0.5970

As can be seen from Table 4, it is presented for two decision-making modes. In the first case, the importance of the cost objective function is more significant than that of the other objective functions (the weight coefficient of this objective function is higher). However, the importance of the EENS and VDI index is assumed to be the same. Under these conditions, solution number 2 is chosen as the preferred solution. In the second case, the weight coefficients of all objective functions are considered the same. In other words, importance of all objective functions for the network operator is the same. Under these conditions, solution 6 is selected as the final solution. Table 5 shows this solution's optimal values.

As can be seen from Table 5, each of the decision variables is optimally determined in each period of the network operation. This solution is known as a solution that has made a reasonable compromise between different objective functions. On the other hand, it is resistant to any uncertainty in the network and can be dynamically used by the network operator.

Table 5: optimal values of decision-making variables

Decision variables	Study period							
	1^{th}	2^{th}	3^{th}	4^{th}	5^{th}	6^{th}	7^{th}	8^{th}
Z_{SW_1}	6	7	6	6	5	7	6	7
Z_{SW_2}	11	10	13	14	10	10	14	14
Z_{SW_3}	13	13	21	21	14	13	21	21
Z_{SW_4}	17	26	26	26	25	25	27	26
Z_{SW_5}	26	30	31	30	30	30	31	30
Z_{ESS_1} (kW)	16.56	10.49	-23.61	-5.18	-21.18	38.18	-3.05	14.98
Z_{ESS_2} (kW)	2.94	5.51	-15.60	-9.80	10.05	16.00	-4.60	-4.65
Z_{ESS_3} (kW)	10.18	-19.40	10.12	0.5489	10.18	2.56	-26.9	20.16
Z_{Cap_1} $(kVAr)$	34.30	41.90	39.35	70.14	35.50	56.80	65.10	32.65
Z_{Cap_2} $(kVAr)$	51.94	59.10	53.26	54.48	93.26	50.68	64.30	26.90

Fig. 6 shows the charging and discharging state of storage for each operation period. In this study, the charge state is assumed to be a negative sign and the discharge state is considered a positive sign. This figure shows that storage is often charged during low energy price hours. Meanwhile, as energy prices become more expensive, storage devices are usually in a state of discharge. Table 6 presents statistical information related to cost in different periods, which is very important in risk management and knowing the number of changes in the objective function due to the uncertainties above.

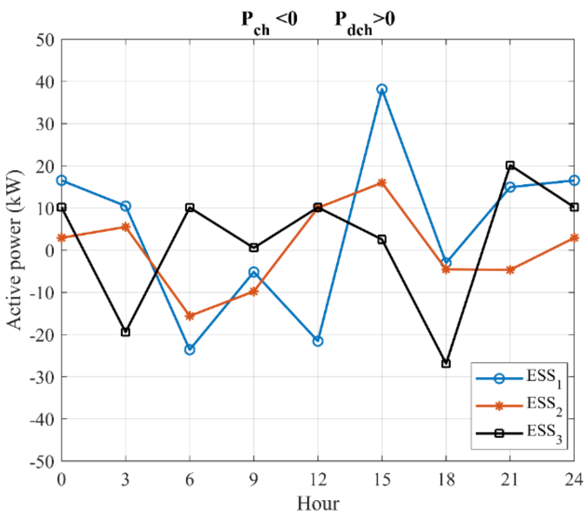

Fig. 6: The charging and discharging state pf storage for each operation period.

Table 6: Operation cost statistical information

Period	$E[\,]$	$\sigma[\,]$
1^{th}	328.91	14.36
2^{th}	335.45	14.61
3^{th}	325.08	18.90
4^{th}	404.68	23.40
5^{th}	510.95	27.90
6^{th}	468.80	25.62
7^{th}	689.59	30.48
8^{th}	658.12	30.01

In general, the results obtained in this section showed that the proposed study method in solving the problem of energy management along with the optimal rearrangement of distribution networks with the goals of reducing the cost of operation, including the cost of purchasing energy from the upstream network and reducing switching costs, improving the reliability index in the form of an index EENS and VDI enhancements are very effective. Considering a wide range of uncertainties and including correlations between uncertain input variables leads to providing more reliable solutions. Meanwhile, providing a set of optimal solutions gives the network operator more flexibility in decision-making.

Conclusion

In this study, the MOPSO method was shown to provide a good performance in solving the energy management problem along with the rearrangement of distribution networks. This method, with the ability to provide a set of solutions based on the Pareto front, gives more decision-making power to the network operator. The solutions provided by this method can be summarized in four modes. The solution chosen as the best solution from the cost of operating point of view reduced the value of this objective function by 10.32%. At the same time, the EENS and VDI indices improved by 7.72% and 18.93%, respectively. The solution obtained as the best solution from the reliability improvement point of view was able to improve the value of this objective function by 19.48%. Meanwhile, network operation cost for this situation has increased by 2.57% and VDI has also improved by 9.23%. The solution chosen as the best solution from the VDI point of view reduced the value of this objective function by 21.41%. Meanwhile, this solution improved the operating cost and EENS indices by 8.97% and 9.23%, respectively. By applying TOPSIS to the set of solutions obtained for the problem in question and considering the same weighting factor for all objective functions, a solution was obtained that can be said to be a balanced solution for the situation. Because it guarantees the relative improvement of all objective functions, this solution has improved the operating cost value by 4.50%, the EENS index value by 13.07% and the VDI value by 18.85% compared to the initial conditions. The effectiveness of the scenario generation method was proved as one of the probabilistic evaluation methods in this problem. This method has a much higher speed than methods like MCS. Meanwhile, its relative error rate in comparison of statistical moments compared to the MCS method as the reference one is appropriate and acceptable. The correlation between non-deterministic input variables affects the distribution and extraction of non-deterministic samples. Therefore, it can be said that the problems' uncertainties are more severe, and the obtained solutions are closer to reality. Changing the extraction of input samples effectively solves the problem. Therefore, all the obtained solutions based on the Pareto front in this problem are more resistant

Author Contributions

All of the authors carried out the theoretical and simulation results and wrote the manuscript.

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Conflict of Interest

The authors declare no potential conflict of interest regarding the publication of this work. In addition, the ethical issues including plagiarism, informed consent, misconduct, data fabrication and, or falsification, double publication and, or submission, and redundancy have been completely witnessed by the authors.

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