IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 31 March 2024, accepted 19 April 2024, date of publication 29 April 2024, date of current version 11 June 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3394868

RESEARCH ARTICLE

Multi-Criteria Decision Making in Optimal Operation Problem of Unbalanced Distribution Networks Integrated With Photovoltaic Units

RAMIN EBADI[1], F. M. ABOSHADY[2,3], (Senior Member, IEEE), OGUZHAN CEYLAN[4], (Member, IEEE), IOANA PISICA[2], (Senior Member, IEEE), AND AYDOGAN OZDEMIR[5], (Senior Member, IEEE)

[1]Department of Electrical Engineering, İstanbul Technical University, 34469 İstanbul, Turkey
[2]Department of Electronic and Electrical Engineering, Brunel University London, UB8 3PH Uxbridge, U.K.
[3]Electrical Power and Machines Engineering Department, Tanta University, Tanta 31527, Egypt
[4]Management Information Systems Department, Kadir Has University, 34083 İstanbul, Turkey
[5]Department of Electrical and Electronics Engineering, Kadir Has University, 34083 İstanbul, Turkey

Corresponding author: Ioana Pisica (ioana.pisica@brunel.ac.uk)

This work was supported in part by "120N996 Implementing Digitalization to Improve Energy Efficiency and Renewable Energy Deployment in Turkish Distribution Networks" Project organized by Tubitak and the British Council under Grant 2551; in part by the Newton Fund Institutional Links Grant through the Newton-Katip Çelebi Fund Partnership under Grant 623801791; and in part by the U.K. Department for Business, Energy and Industrial Strategy and Tubitak and delivered by the British Council.

ABSTRACT The use of renewable energy sources is increasing day by day due to their economic and environmental benefits. However, improper penetration of renewable energy into power grids can lead to problems such as over-voltages and higher active power losses. Therefore, the voltage regulation problem in distribution networks is critical due to the increasing integration of renewable energy sources. On the other hand, an increase in renewable energy penetration leads to lower operational costs due to decreased energy purchases from the overhead grid. Therefore, it can be challenging for distribution system operators (DSOs) to decide the trade-off between more Photovoltaic (PV) integration for cost minimization or less penetration to minimize voltage deviation from a rated value. In this study, we formulated this trade-off as a novel multi-objective optimization framework, aiming to minimize operating costs and voltage deviations from a rated value in an unbalanced distribution grid. The proposed formulation is applied to the modified IEEE 34-bus unbalanced distribution network, where the ε-constraint method is utilized for solving the resulting multi-objective optimization problem along with the Exterior Penalty Functions (EPF) method. The simulation results show that the proposed approach provides the DSO with a better view of decision-making in the optimal operation of the distribution networks.

INDEX TERMS Unbalanced distribution networks, photovoltaics, Volt/Var control, cost minimization, multi-criteria decision making, ε-constraint method.

NOMENCLATURE

INDEXES

gr	Grid.
i, j	Nodes/buses.
k	Iteration count.
l	Line section.
m	Set of adjacent lines to node i.
t	Time (hour).

PARAMETERS

λ, μ	Penalty multipliers.
L	Total load of the system.
P_{PV}^{max}	Upper limit of PV active power output.

The associate editor coordinating the review of this manuscript and approving it for publication was Mauro Gaggero.

PC	Cost of power purchased from the grid.
Q_{PV}^{max}	Upper limit of PV reactive power output.
Q_{PV}^{min}	Lower limit of PV reactive power output.
S_i	Total apparent power injection at node i.
T	Total number of hours in the scheduling horizon.
TP^{max}	Upper limit of tap position set points.
TP^{min}	Lower limit of tap position set points.
V^{max}	Upper limit of node voltage magnitudes.
$V^{\min}$	Lower limit of node voltage magnitudes.
Y_i	Total shunt admittance connected to node i.
Z_l	Series impedance matrix of branch l.

VARIABLES

$f(x)$	Objective function.
$g(x)$	Equality Constraints.
$h(x)$	Inequality constraints.
I_i	Total current injection at node i.
J_l	Current flowing through line section l.
J_m	sum of currents flowing on the adjacent branches of node i.
P_{gr}	Power purchased from grid.
P_{loss}	Active power losses of the system.
P_{PV}	Active power output of PV.
Q_{PV}	Reactive power output of PV.
S_{PV}	Apparent power.
TP	Tap positions.
V	Voltage magnitudes.

I. INTRODUCTION

A. MOTIVATION

Analysis of the operation problem of unbalanced distribution networks, which can be considered as intermediaries between the transmission system and consumers, can be considered as a well-studied topic. However, in recent years, DSOs are facing new challenges due to the penetration of new technologies, including renewable energy sources (RESs), energy storage devices, electric vehicles, etc. [1]. On the one hand, integrating these resources provides more efficient and flexible operation of the distribution networks. On the other hand, the bidirectional power flow of these resources can cause various problems, such as over-voltages due to surplus active power generation in the distribution networks [2].

Recently, the penetration of renewable energy into distribution grids has experienced an upward trend due to various economic and environmental benefits. Based on a report by the International Energy Agency (IEA), renewable energy capacity is expected to increase by 2400 GW between 2022 and 2027 [3]. Therefore, operational problems arising from this increasing trend of renewable energy integration into the distribution networks must be controlled effectively.

Moreover, it is known that in real distribution networks, which generally have a radial structure, the voltage magnitude decreases from the source to the feeder end, causing an under-voltage problem. A basic rule of circuit theory states that a voltage deviation from the rated value is undesirable since this phenomenon leads to higher power losses. In addition, voltage deviation can also affect other power system behaviors, such as transient stability [4], [5]. Therefore, minimizing the voltage deviation from the rated value can be considered one of the most important issues in distribution system operation. Based on a standard provided by the IEEE [6], this margin is considered ± 5 % from the rated value. For this purpose, conventionally, tap changer voltage regulators and switchable capacitor banks have been used to control the voltage magnitudes along the feeder [7], [8]. However, these methods may not be able to regulate the voltage magnitudes efficiently in unbalanced distribution networks in case of high renewable penetration into the grid. Moreover, regulating performance deteriorates because of the aging of those devices due to frequent switchings along their operational life [9].

As mentioned earlier, the bidirectional power flow resulting from RESs integration causes some challenges to DSO. However, the DSO can utilize this bi-directional flow to control the voltage of distribution networks using the reactive power capability of the Photovoltaic (PV) Units composed of single or several solar panels connected through smart inverters. The process can be described as the absorption and injection of reactive power, resulting in a voltage drop or rise in the event of over- or under-voltage cases, respectively [10].

In addition, energy supply from the upper-level transmission networks comes at a cost to DSOs, which may be more expensive than the supply provided by Distributed Energy Resources (DERs) [11]. Another challenge for operators is minimizing the distribution networks' operating costs. This challenge becomes even more complex when dealing with integrated distribution systems with renewables. In other words, the DSO tends to use more renewables since their operating costs are close to zero and import less energy from the upper stream grid. On the other hand, integrating more renewables leads to over-voltage problems, as mentioned earlier. This is the point where the DSO has to make a trade-off between voltage deviation and operating costs.

In this paper, we have explored this challenge. In general, the voltage control problem of distribution networks can be formulated as an optimization problem [12]. There are two important issues in this regard: formulating the problem and solving it with an appropriate method. Various optimization approaches have been presented in the literature, including the Exterior Penalty Function (EPF) method [13] as a gradient-based approach. Furthermore, since there may be more than one objective, such as minimizing operating costs and improving voltage profiles, the problem can be formulated as a multi-objective optimization process. Several methods, including the weighted approach and the ε-constraint method, were studied for solving the multi-objective optimization problems, and it was shown that they had their advantages and disadvantages [14].

B. LITERATURE REVIEW

Several studies have been carried out on the problem of voltage control in unbalanced distribution networks. The presented models have studied the volt/var control approaches from different aspects and with different control methods.

In [15], the authors investigated the over-voltage problem caused by integrating DERs in secondary distribution networks in residential areas. Since secondary distribution networks had a high R/X ratio and required more reactive power to minimize voltage deviations than primary networks, the proposed model reduced the need for reactive power absorption only by DERs. The authors in [16] presented a real-time distributed control method for low-voltage grids that considered the dynamic optimal power flow, a model-predictive control scheme, and the optimal use of renewable generation and energy storage. The results confirmed that the approximated power flow had a lower error than the backward-forward-sweep (BFS) power flow method. In [17], the authors investigated the distributed voltage control based on local measurements and neighborhood communication. Simulation results showed that the proposed model leads to the optimal voltage of the busses even with asynchronous or delayed communication and a linear power flow scheme. In [18], a comprehensive volt/var control framework was presented considering load tap changers, capacitors, and PV inverters. The authors used a robust optimization method to address uncertainties and minimize power losses in the study.

On-line volt/var control of unbalanced distribution systems by the projected Newton method was investigated in [19] with the penetration of DERs. Voltage regulators and their magnetizing reactance are used in [9] for voltage regulation of unbalanced distribution systems using the augmented Lagrangian multipliers method as an optimization approach. In [20], a two-stage voltage control method using reactive power control and load tap changers was proposed, considering voltage profile improvement and delivery losses in the first stage and voltage stability in the next stage. In [21], a volt/var control scheme using the EPF method as an optimization approach was presented, which considered the PV systems' reactive power and the voltage regulators' tap position. Compared to the IEEE standard voltage control method, the method required low reactive power to solve the voltage problem. However, minimizing the operation cost during normal conditions was not considered. The use of smart inverters and the required techniques were analyzed in [22].

The authors in [23] have presented a dispatch model for a renewable-integrated microgrid in both off-grid and on-grid modes considering five different dispatch control schemes. HOMER Pro platform was used to clarify the optimal combination of the system from technical, economic and environmental points of view. In addition, the DIgSILENT PowerFactory was utilized to elaborate the reactive power, frequency, and bus voltage responses. It is notable that the HOMER Pro platform was also compared to the particle swarm optimization (PSO), genetic algorithm (GA), ant colony optimization (ACO), and flower pollination algorithm (FPA) and the results validated the efficiency of the proposed model. For evaluating the effect of weather, consumer demand and industrial loads, an ancillary voltage control framework was presented in [24] for a renewable-based microgrid. Obtained results have shown that the introduced intelligent adaptive controller results in maintaining stable input voltage for secondary networks. The challenges of integrating renewable sources including PV and wind power in the conventional power systems and islanded microgrids were assessed in [25]. The Hybrid Firefly Genetic Algorithm was utilized as an effective optimization approach in [26] in the energy management problem of a standalone hybrid microgrid. Results validated the efficiency of the proposed model in minimizing the annual cost of the system.

Some studies have presented machine learning techniques as a novel method to solve the voltage control problem in distribution networks. The authors in [27] presented a model for real-time decision-making in case of sudden voltage deviations due to PV system output power variations. First, based on the surrogate model, the supervised training algorithm was used to determine the relationship between the voltage deviation of the busses and the power injection at the nodes. In the following stage, the optimal approach for voltage control was determined using the deep reinforcement learning technique. To reduce the need for precise parameters in distribution networks, a physical model-free voltage control scheme was presented in [28]. In particular, the presented model could handle both the fast time scale using the PV inverters and the slow time scale using the tap changers and capacitor banks.

To minimize the operating costs of the distribution network, a multilevel optimization model was presented in [29]. In this study, the uncertainties of renewable generation and load were modeled by Information Gap Decision Theory (IGDT). In [30], a multi-objective optimization scheme was presented to minimize the distribution system's operating cost and power loss considering various distributed generators, including PV and wind power. Reference [31] evaluated the technical and economic analysis of active distribution networks fed by an external grid by a multi-objective optimization model. A multi-criteria framework was presented in [32] to improve the voltage profile and minimize operation, maintenance, and investment costs in an integrated distribution system with renewable energy. In [33], a multi-objective optimal Volt/VAR control scheme is presented to optimize the power loss and the cost of adjusting the grid's voltage control assets. In the mentioned study, the capacitor bank switches, tap position of on-load tap changer transformers, voltage regulators' taps, and active and reactive power set-points of prosumer distributed energy resources have been taken into account.

The ε-constraint method was used in [34] to solve the multi-objective optimization problem considering costs and greenhouse gas (GHG) emissions. The simulation results showed that the proposed model could effectively contribute to minimizing the two objective functions. In [35], a multi-objective optimal power flow program was presented and solved using the ε-constraint method. The mentioned model was tested on various systems, including the IEEE 30, 57, and 118 bus test systems, and the results confirmed the model's superiority over other similar methods. To minimize the frequency deviation in a battery storage system, the EPF optimization method was used in [36] to solve the nonlinear programming (NLP) problem. The EPF method was used in [37] for the techno-economic analysis of a hybrid power system of PV and fuel cells.

The authors in [38] have presented a multi-objective optimization scheme for dispatching the PV inverters, on-load tap changers, and capacitor banks. The advantage of the proposed model over the previous studies is proposing a distributed dispatch method that has a low computational burden. However, in this study, the objective is to reduce the voltage magnitude and losses. On the other side, the proposed method for solving the multi-objective optimization problem is the weighted sum approach. A comprehensive comparative study for dealing with multi-objective optimization problems was introduced in [39] in which the authors have considered various optimization methods inclusive of the Genetic Algorithm, Firefly Algorithm, Particle Swarm Optimization, and a novel hybrid of the Firefly and PSO algorithms for minimizing the annual cost of energy systems, greenhouse gas emissions, and the total Dump energy. Distributed leader-follower voltage control method is proposed in [40] by using the smart inverters of PV units. The aim of the presented model was to minimize the total power consumption of the system, and the results validated that. A chance-constrained voltage control method for unbalanced distribution networks was presented in [41], in which the authors have considered a data enrichment approach to deal with the uncertainty of load and PV generation. The objective of the mentioned study was to reduce the total power consumption of the grid. As can be understood, multi-objective optimization for minimizing the total operation cost and voltage deviation from the rated value of the unbalanced distribution networks was not studied extensively in the literature. Moreover, considering the ε-constraint method as an efficient approach for dealing with multi-objective optimization problems was not in the scope of the mentioned studies investigating the distribution systems' voltage control problem.

Despite several methods presented in the existing literature, the improvement of the solution methods from the aspects of accuracy, convergence, computation speed, and efficiency in real applications can be considered an open problem. Moreover, providing a comprehensive control framework that considers more than one crucial operational criterion has not been extensively studied.

C. CONTRIBUTIONS

Based on the above discussion, the techno-economic analysis of renewable-integrated unbalanced distribution networks is an important issue that can be considered an open problem, requiring additional efforts. In this study, we have analyzed the modified IEEE 34-bus unbalanced distribution system from both technical and economic points of view. For this purpose, a multi-objective optimization framework is presented, considering the cost of energy provided by the transmission grid on one side and the deviation of the voltage magnitudes from the rated flat value on the other as the objective functions. As we know, previous studies have not extensively investigated the presented model. Specifically, the presented study contributes to the existing body of knowledge as follows:

1) A techno-economic analysis of a RES- integrated IEEE 34-bus unbalanced distribution network is studied, providing the DSO with a comprehensive vision for decision-making on the operational problem.
2) The reactive power of PV systems and voltage regulators are considered arms for voltage control of the proposed unbalanced distribution system.
3) A multi-objective optimization scheme is considered to minimize the energy cost from the grid and the voltage deviation from the nominal value simultaneously. The ε-constraint method deals with the presented multi-objective optimization problem.
4) Exterior penalty function (EPF) optimization method is the main approach to solving the optimization problem.

The rest of the paper is organized as follows. The methodology and problem statement of the proposed model is described in section II. Case studies and simulation results are presented and discussed in section III. Finally, section IV concludes the paper.

II. PROBLEM FORMULATION

The operation of a power system can be formulated as an optimization problem with an appropriate method to solve the power flow problem of the system. Considering the type and topology of a power system, various classical and novel methods for solving the power flow problem of the system are presented by researchers [42], [43]. In this section, a suitable power flow approach for the intended system is first presented. Then, the optimization framework for the optimal operation of the unbalanced distribution system is explained. Finally, it is illustrated how the ε-constraint method can be applied efficiently to solve a multi-objective optimization problem.

A. BACKWARD-FORWARD SWEEP (BFS) METHOD

The radial nature of the distribution grids with high R/X ratios makes the conventional Newton-Raphson (NR) method for power flow a nearly infeasible approach to converge to an accurate result. Therefore, another efficient method is required for solving the power flow problem of the unbalanced distribution networks, which has better convergence performance and accuracy rate. The backward-forward-sweep (BFS) power flow method is one of those ones

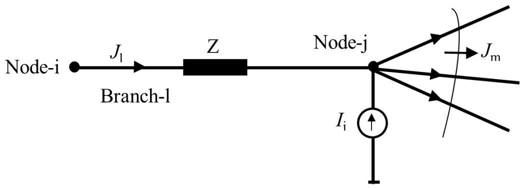

FIGURE 1. Representation of branch-l in BFS method.

that can satisfy the above criteria. The procedure starts with defining the series impedance matrix of a line segment as Z_l for phases 1, 2, and 3 and the admittance of all shunt elements at node i as Y_i as shown in (1) and (2) [44].

$$Z_l = \begin{pmatrix} Z_{l,11} & Z_{l,12} & Z_{l,13} \\ Z_{l,21} & Z_{l,22} & Z_{l,23} \\ Z_{l,31} & Z_{l,32} & Z_{l,33} \end{pmatrix} \tag{1}$$

$$Y_i = \begin{pmatrix} Y_{i1} & 0 & 0 \\ 0 & Y_{i2} & 0 \\ 0 & 0 & Y_{i3} \end{pmatrix} \tag{2}$$

To initialize the BFS, the root node is treated as a slack bus, and the voltage of the other busses is considered equal to the root node. The iterative BFS is developed in three steps. The three steps of k^{th} BFS iteration is explained using a representative branch-l connected between node-i and node-j as in Fig. 1.

1) Defining the nodal currents:
In the first step, the nodal currents are calculated by (3) using the nodal voltages, which are initially 1.0 p.u., depending on the connected load type.

$$\begin{pmatrix} I_{i1}^{(k)} \\ I_{i2}^{(k)} \\ I_{i3}^{(k)} \end{pmatrix} = \begin{pmatrix} (S_{i1}/V_{i1}^{(k-1)})^* \\ (S_{i2}/V_{i2}^{(k-1)})^* \\ (S_{i3}/V_{i3}^{(k-1)})^* \end{pmatrix} - Y_i \begin{pmatrix} V_{i1}^{(k-1)} \\ V_{i2}^{(k-1)} \\ V_{i3}^{(k-1)} \end{pmatrix} \tag{3}$$

2) Calculating the branch currents- Backward sweep:
Branch current calculations start from the last bus in each feeder (end nodes) towards the upstream direction (root node). As illustrated in Fig. 1, Kirchhoff's current law (KCL) is used for finding the current of the branch l using (4). Note that J_m is the sum of currents flowing on the adjacent branches of node j.

$$\begin{pmatrix} J_{l1}^{(k)} \\ J_{l2}^{(k)} \\ J_{l3}^{(k)} \end{pmatrix} = - \begin{pmatrix} I_{j1}^{(k)} \\ I_{j2}^{(k)} \\ I_{j3}^{(k)} \end{pmatrix} + \begin{pmatrix} J_{m1}^{(k)} \\ J_{m2}^{(k)} \\ J_{m3}^{(k)} \end{pmatrix} \tag{4}$$

3) Calculating the nodal voltages- Forward sweep:
Bus voltages are calculated starting from the root node towards the downstream nodes (end nodes) using Kirchhoff's voltage law (KVL). (5) is written for any downstream node voltage-j, using the upstream node voltage-i and branch current-l, where l is the branch index connected between nodes i and j.

$$\begin{pmatrix} V_{j1}^{(k)} \\ V_{j2}^{(k)} \\ V_{j3}^{(k)} \end{pmatrix} = \begin{pmatrix} V_{i1}^{(k)} \\ V_{i2}^{(k)} \\ V_{i3}^{(k)} \end{pmatrix} - Z_l \begin{pmatrix} J_{l1}^{(k)} \\ J_{l2}^{(k)} \\ J_{l3}^{(k)} \end{pmatrix} \tag{5}$$

All the branch currents and node voltages will be calculated at the end of the third step. The sweeping process is terminated if the difference between the node voltages of the last two consecutive iterations is less than a pre-specified threshold value. Otherwise, the next iteration starts at step 1 with the updated node voltages of this iteration.

B. EXTERIOR PENALTY FUNCTION (EPF) OPTIMIZATION APPROACH

The optimum operation of unbalanced distribution networks can be formulated as an optimization problem aimed at minimizing or maximizing desired objective functions. Choosing appropriate methods in terms of convergence speed and accuracy to solve the resulting optimization model is a crucial issue in operation problems. For this purpose, one of the suitable options is the EPF optimization approach. EPF is effective for problems with both equality and inequality constraints. It allows the optimization process to proceed even when the constraints are violated initially, gradually penalizing such violations in the objective function to drive the optimizer toward feasible solutions. EPF is relatively straightforward to implement compared to some other constraint-handling techniques like interior penalty or barrier methods. This simplicity can make it an attractive choice for certain problems. In many cases, exterior penalty methods converge to a feasible solution. As the penalty parameter increases, the optimization process tends to produce solutions that satisfy the constraints more closely. In addition, the penalty parameter can be adjusted to control the trade-off between satisfying the constraints and optimizing the objective function. This adjustability allows for fine-tuning the optimization process based on problem-specific requirements [45]. In general, a constrained optimization problem can be described as follows:

$$\begin{aligned} \text{maximize} \quad & f(x) \\ \text{subject to} \quad & g(x) = 0 \\ & h(x) \leq 0 \end{aligned} \tag{6}$$

In the EPF method, the constrained optimization problem is transformed into a sequential unconstrained model. In addition, a penalty multiplier is added to satisfy the constraints.

Finally, the resulting problem is as follows:

$$\text{maximize } F = f(x) + \lambda g(x) + \mu h(x) \tag{7}$$

C. ε-CONSTRAINT METHOD

Based on the decision stage in which the decision maker defines the preferences, multi-objective optimization approaches can be classified into priori, interactive, and posteriori schemes. In comparison to priori methods, including the weighted approach, the interactive and posteriori methods provide more information for the decision-maker. One of the advantages of the ε-constraint method over the weighted method is that it is possible to obtain an efficient solution in each run. In the weighted method, it is sometimes required to spend more runs since many weight combinations may result in the same efficient solution. Therefore, the ε-constraint method results in a rich solution set. In addition, the ε-constraint approach can provide unsupported efficient solutions in multi-objective integer and mixed integer programming frameworks, while the weighted method is not able to deal with this. The other advantage of the ε-constraint method is that the scaling and the range of objective functions do not affect the solutions. As a result, it is not necessary to scale the objective functions to a common range. Moreover, the number of efficient results is under control in the ε-constraint method, however, this is not a straightforward process in the weighted method. Finally, ε-constraint has been considered as an effective method to deal with the problems with non-convex Pareto fronts [46].

The basic structure of a multi-objective optimization problem with α objective functions and β constraints can be considered as follows:

$$\begin{aligned} &\text{maximize} \quad (f_1(x), f_2(x), \ldots, f_\alpha(x)) \\ &\text{subject to} \quad (g_1(x), g_2(x), \ldots, g_\beta(x)) \end{aligned} \tag{8}$$

Here g includes either equality or inequality constraints. Among several methods for solving multi-objective optimization problems, including weighted sum, lexicographic, etc., the ε-constraint method is considered one of the most efficient approaches for defining a Pareto front and determining the trade-off solution [47]. To apply the ε-constraint formulation to the main multi-objective model, one of the α objective functions is considered the main objective, and the other functions are held as constraints. Then, various lower or upper bounds (based on the main problem being a maximization or minimization problem) are aligned to the objectives, which are transformed into constraints. Finally, the resulting single-objective optimization problem with β+α-1 constraints is solved by the EPF optimization method. If we consider the overall problem as maximization, the resulting model looks as follows:

$$\begin{aligned} &\text{maximize} \quad f_1(x) \\ &\text{subject to} \quad (g_1(x), g_2(x), \ldots, g_\beta(x)) \\ &\qquad\qquad (f_2(x) \geq \varepsilon_1, f_3(x) \geq \varepsilon_2, \ldots, f_\alpha(x) \geq \varepsilon_{\alpha-1}) \end{aligned} \tag{9}$$

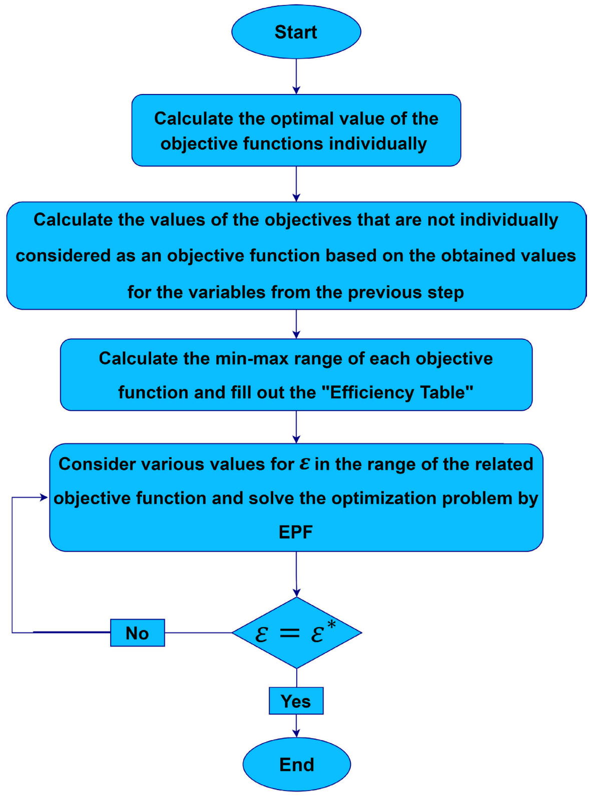

FIGURE 2. Solution algorithm of ε-constraint method.

It is worth noting that the factors of the ε-constraint method (ε_1,ε_2,ε_3,...) will get different values during the solution process. To determine the values of these factors, the min-max range of the other n-1 objective functions must be calculated. The detailed algorithm for implementing the ε-constraint method is shown in Fig. 2.

D. IMPLEMENTATION OF MULTI-OBJECTIVE OPTIMIZATION FRAMEWORK FOR DISTRIBUTION SYSTEM OPERATION

This study proposes a techno-economic analysis of unbalanced distribution networks that consider both the minimization of voltage deviations from rated values and the cost of energy from the network, which are considered as operating costs of the distribution system. The multi-objective optimization model is constructed from the two objective functions as follows:

$$\text{minimize} \quad f_1(x) = \sum_{i=1}^{I} (1 - V_i)^2 \quad \forall\, \Delta t \tag{10}$$

$$\text{minimize} \quad f_2(x) = P_{gr} * \Delta t * PC \quad \forall\, \Delta t \tag{11}$$

Note that the objective functions shown in (8) and (11) represent the voltage deviations from 1 pu., and the operation cost of the distribution network. With the first objective function, we aim to obtain as flat as possible voltage profile, by bringing the voltage magnitudes of all nodes closer to 1 p.u. The second objective function is used to minimize the operation cost of the distribution network, by minimizing the amount of power being purchased from the upstream grid [30], [31].

E. CONSTRAINTS

There are several technical constraints regarding the operation of distribution networks. The voltage magnitudes of the network are desired not to exceed certain limits, which is assumed to be ±5 % of the rated voltage levels in this study. Therefore, the upper and lower limits are 1.05 p.u. and 0.95 p.u., respectively. Equation (12) demonstrates the voltage magnitude constraint.

$$V^{min} \leq V_{i,t} \leq V^{max} \tag{12}$$

The voltage regulator's tap positions must remain within the specified boundaries, between −16 and +16, to ensure stable and safe operation as shown in (13) [48], [49]. These limits define the acceptable range for voltage adjustments, preventing the system from experiencing over-voltage or under-voltage conditions. Adhering to these boundaries safeguards the equipment, maintains optimal performance and prevents potential damage that could arise from voltage deviations beyond the prescribed limits. Note that the tap positions can only take integer values.

$$TP^{min} \leq TP_t \leq TP^{max} \tag{13}$$

The reactive power support from the inverter has a minimum and a maximum limit that the operating strategy must respect. In this study, we assume that this limit is given by (14) and (15). The reactive power limits in (14) can be found by leaving $Q_{PV,t}$ alone in (15) for each time step t. In this study, we assume that reactive power consumption or production can be provided through inverters when they are at least 5% of their rated power as specified in IEEE-1547 [50].

$$Q^{min}_{PV,t} \leq Q_{PV,t} \leq Q^{max}_{PV,t} \tag{14}$$

$$S^2_{PV,t} \geq Q^2_{PV,t} + P^2_{PV,t} \tag{15}$$

In addition, the DSO decides on the amount of integrated PV active power, and this active power must not exceed the maximum capacity of the installed PV system. Equation (16) illustrates this constraint.

$$P_{PV,t} \leq P^{max}_{PV,t} \tag{16}$$

Finally, the power balance constraint states the equilibrium between the generation, including the support from the upstream grid, and consumption in the distribution network. It is formulated as follows:

$$P_{gr} + P_{PV} + P_{loss} = \sum_{i=1}^{I}(L) \quad \forall t \tag{17}$$

The presented study comprises three main stages. At first, load flow studies are implemented on the IEEE 34-bus system to define the existing voltage problems in the system and provide baseline data for comparing results. Afterward, PV penetration is taken into account, and an optimization framework is built up based on the objective function and constraints introduced in the problem formulation section. The proposed model is a single-objective optimization problem aiming to minimize the voltage magnitude deviation from the rated value considering the required operational constraints. Finally, the optimization framework is updated based on the requirements of the ε-constraint method to reflect a multi-objective optimization scheme. The pseudocode defining the procedure for solving the multi-objective optimization problem in this stage is depicted in Algorithm 1. The aim of stage 3 is to simultaneously minimize the voltage deviations from the rated flat value and the operation cost of the grid with necessary constraints. At the end of this stage, a trade-off table between the objective functions is provided for decision-making strategy. Fig. 3 depicts the overall procedure and flow of the paper.

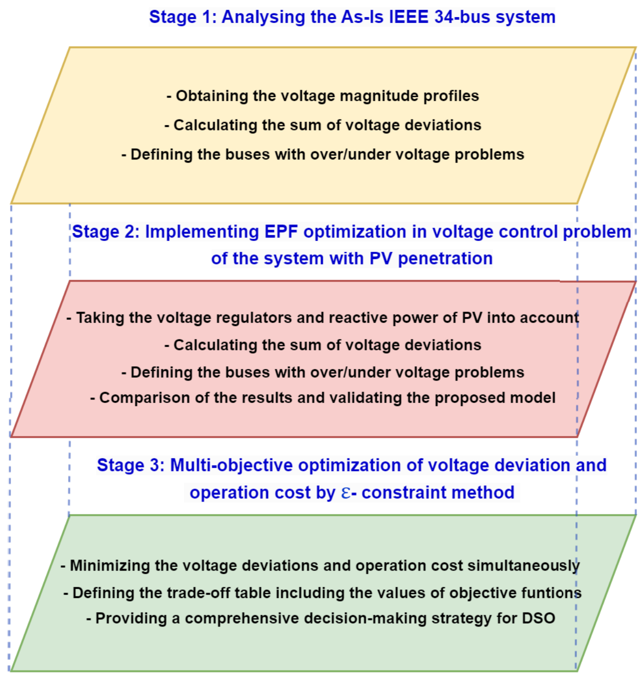

FIGURE 3. Overall procedure of the paper.

III. SIMULATION RESULTS

We performed hourly simulations on a modified IEEE 34-bus test system [51]. The single-line diagram as well as the inputs and outputs of the problem are shown in Fig. 4. Two voltage regulators are considered between the busses 814-850 and 832-852. In addition, an inverter-interfaced PV unit with a rated power of 300 kW is considered at terminal node 890. The scaled PV generation and load profiles (coefficients) are shown in Fig. 5 with a resolution of 1 hour [52], [53].

As known, power electronics-based inverters are able to inject/absorb reactive power to the system much faster compared to the mechanical-based conventional devices such as tap changer voltage regulators. In this study, the simulation time resolution was set to one hour to show the efficiency of the coordinated operation of both the mechanical and power

Algorithm 1 Solution of the Multi-Objective Problem

Input:
  Objective function upper/lower bounds $f_{low}, f_{up} \in R$
  Increment of $\varepsilon, \delta \in R$
  Initial point for EPF, X^1
  Maximum number of iterations, N^{max}
  Convergence and stopping tolerance, τ
  Initial penalty multipliers, μ^0, λ^0
  Scaling factor for multipliers, C_h, C_g
  Iteration counter, $cnt = 1$
  Pareto optimal solutions space, $p = \phi$
  Initialize $\varepsilon = f_{up}$
while $\varepsilon \geq f_{low}$ **do**
  $X^{cnt} = DFP\ \ F(\mu^{cnt}, \lambda^{cnt}, \varepsilon - \delta, \varepsilon)$
  if $g_b\ \ (b = 1, 2, \ldots, \beta)$ is satisfied **then**
    Converged
  end if
  $\Delta F = F^{cnt} - F^{cnt-1}$
  $\Delta X = X^{cnt^*} - X^{(cnt-1)^*}$
  if $(\Delta F)^2 \leq \tau$ **then**
    Stop
  else if $\Delta X^T \Delta X \leq \tau$ **then**
    Stop
  else if $cnt = N^{max}$ **then**
    Stop
  end if
  Continue
  $cnt \leftarrow cnt + 1$
  $\mu^{cnt} \leftarrow \mu^{cnt^*} C_h$
  $\lambda^{cnt} \leftarrow \lambda^{cnt^*} C_g$
  $X^{cnt} \leftarrow X^{cnt^*}$
  if $\nexists X' \in P$ such that $x' \succ x$ **then**
    $P = P \cup \{x\}$
  end if
  $\varepsilon = \varepsilon - \delta$
end while
Output: Set of Pareto optimal solutions P

electronics-based devices. Thus the proposed model assumes that the control actions are taken at each hour for this study. Simulations are performed, and the results are discussed for the three case scenarios defined below. Note that the EPF method is used as a solution tool for all cases.

- Case 1 (Base-case)- This operating condition has no voltage control. The purpose of this case is to provide baseline data for comparing results.
- Case 2- In this case, we only aim to minimize the total voltage deviations along a day as the objective function. We utilize the voltage regulator taps and reactive power support of the PV unit to improve the voltage profile.
- Case 3- This case is formulated as a multi-objective optimization to handle both the technical and economic objectives. We aim to minimize the total voltage magnitude deviations from the rated values and energy supply cost by controlling the voltage regulator taps and PV reactive power output. Note that the ε-constraint method is used for this multi-objective optimization framework. By solving the multi-objective model, we aim to provide comprehensive insight for the DSO for decision-making in the operating problem of unbalanced distribution networks.

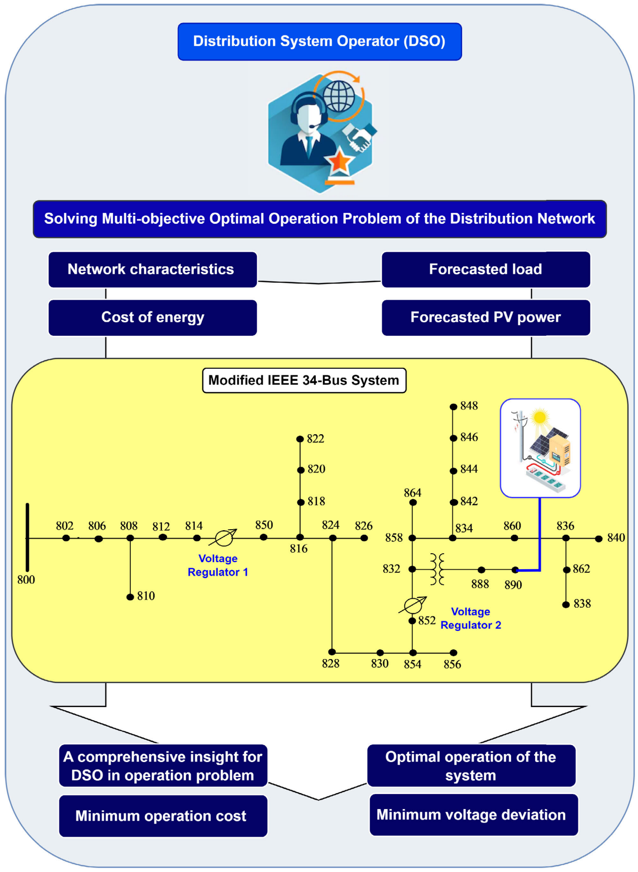

FIGURE 4. The studied system with inputs and outputs of the problem.

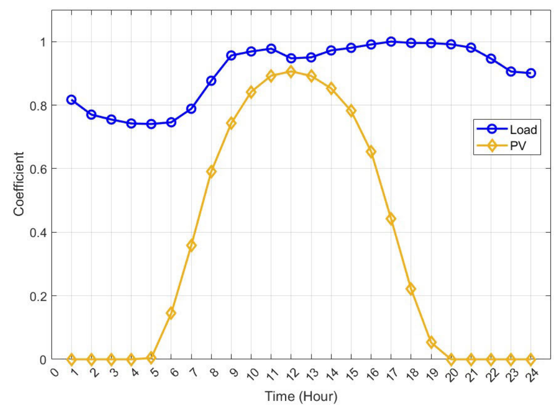

FIGURE 5. Coefficients of hourly load and PV generation.

A. CASE 1

In this case, the normal power flow is performed using the BFS method for the unbalanced IEEE 34-bus distribution

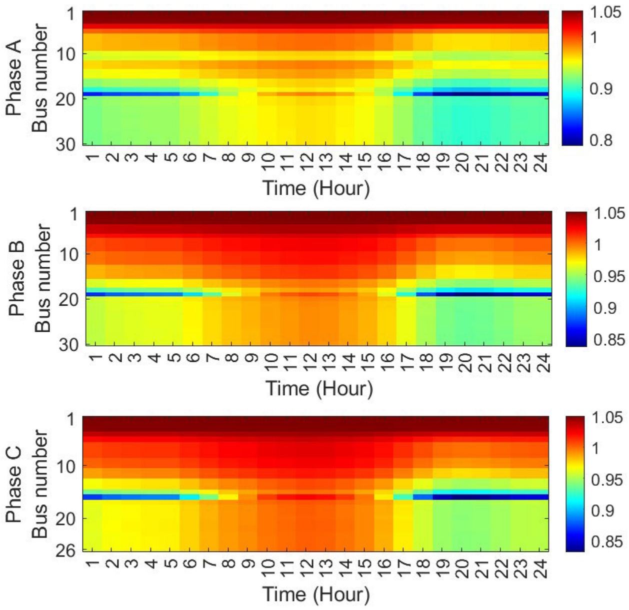

FIGURE 6. Voltage profiles of the system- Case 1.

network. The voltage regulator tap positions are considered to be zero on phases A, B and C. The voltage profiles are depicted in Fig. 6. Moreover, Table 1 provides guidance for the bus numbers on the single line diagram (SLD) and illustrated voltage profiles for all case studies. From Fig. 6, it can be seen that the system has an under-voltage problem due to the radiality of the network. The problem is particularly severe at the feeder end nodes and after 17:00 when the total system load increases. The need for a comprehensive voltage control procedure is evident here, and upcoming case studies will analyze this problem in detail.

B. CASE 2

For this case, we set up a voltage regulation framework for the mentioned unbalanced distribution network. Two voltage regulators, as well as the reactive power support from the PV systems, are considered to improve the voltage profiles. The voltage profile of the system is shown in Fig. 7. From this figure, it can be concluded that by implementing the control method, the voltage profiles of the system have been changed, and the under-voltage problems of the base-case operating conditions have been resolved. Moreover, due to the high PV generation, there are over-voltage problems in a few system nodes. However, as desired, the overall voltage profiles are close to the nominal value of 1 p.u.. It is worth noting that at 19:00, there are some voltage violations on all three phases of terminal node 890. The reason for this phenomenon is that at this time, not only the PV generation is low, but also the load on the system is high and the voltage of the system is controlled only by the voltage regulators, which are not sufficient to eliminate all the under-voltage problems. In order to provide a detailed interpretation of results and validate the efficiency of the proposed model, Table 2 is

TABLE 1. A guide for bus numbers on voltage profiles and the SLD.

Ph "A" Profiles	Ph "A" SLD	Ph "B" Profiles	Ph "B" SLD	Ph "C’ Profiles	Ph "C" SLD
1	800	1	800	1	800
2	802	2	802	2	802
3	806	3	806	3	806
4	808	4	808	4	808
5	812	5	810	5	812
6	814	6	812	6	814
7	850	7	814	7	850
8	816	8	850	8	816
9	818	9	816	9	824
10	820	10	824	10	828
11	822	11	826	11	830
12	824	12	828	12	854
13	828	13	830	13	852
14	830	14	854	14	832
15	854	15	856	15	888
16	852	16	852	16	890
17	832	17	832	17	858
18	888	18	888	18	834
19	890	19	890	19	842
20	858	20	858	20	844
21	864	21	834	21	846
22	834	22	842	22	848
23	842	23	844	23	860
24	844	24	846	24	836
25	846	25	848	25	840
26	848	26	860	26	862
27	860	27	836	-	-
28	836	28	840	-	-
29	840	29	862	-	-
30	862	30	838	-	-

provided in which the total number of voltage violations in case 1 (base case) and case 2 are reported. Moreover, the value of objective function in the two cases are provided. The results show that 701 of 728 voltage violations are eliminated by optimizing the tap-changer positions and PV reactive power outputs. On the other hand, the total voltage deviation decreased to 3.4480, from 6.1940 in case 1, with the proposed optimization model. Note that some unavoidable over- voltage violations occur due to high tap ratios at evening hours and lack of PV reactive power consumption support. Moreover, the hours with no voltage violations are not mentioned in the table. TVV stands for the total number of voltage violations and TVD is the total voltage deviation given by Equation (8).

The injection/absorption of reactive power of the PV unit (inverter) is shown in Fig. 8. Notably, the reactive power

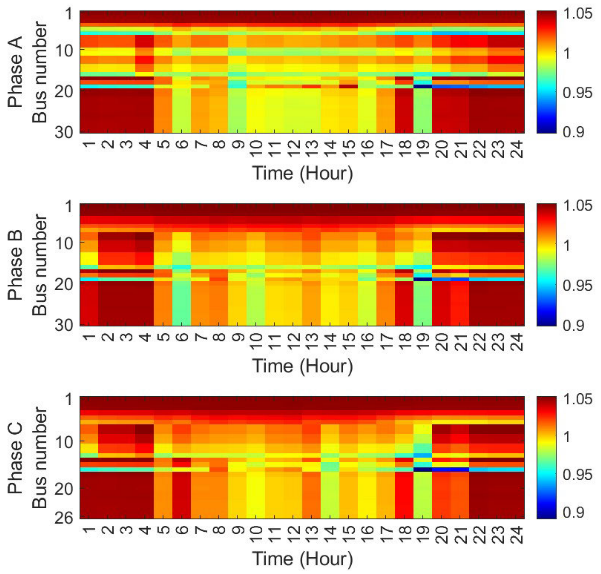

FIGURE 7. Voltage profiles of the system- Case 2.

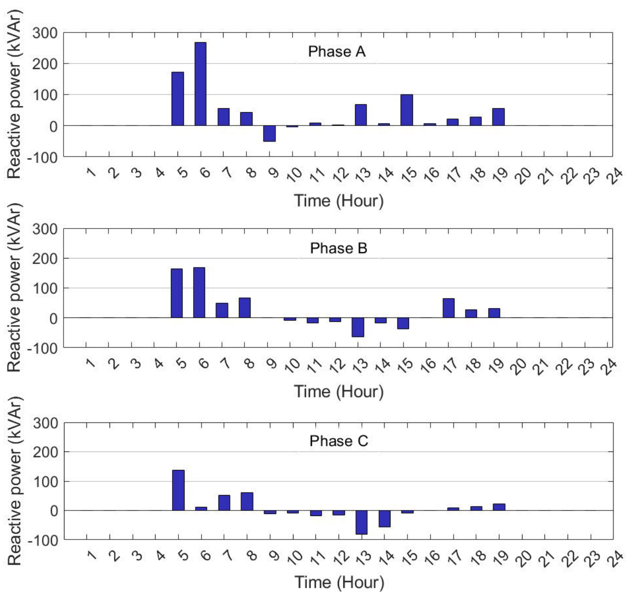

FIGURE 8. Reactive power injection/absorption at bus-890- case 2.

transaction occurs only during the hours when PV generation is present. There will be higher voltage drops along the branches at higher load levels. The PV unit injects higher reactive power during this period to avoid under-voltage problems. Note that the active power injection of the PV unit also contributes to solving the high voltage drop problem. On the other hand, when the load is low and the PV active power injection is high, an over-voltage tendency occurs in the system, and the inverter absorbs the reactive power to solve the problem.

Finally, the tap positions of the voltage regulator are shown in Fig 9. As mentioned earlier, between 1:00 and 6:00 and between 19:00 and 00:00, when there is no PV generation, the voltage regulators are the only way to contribute to the

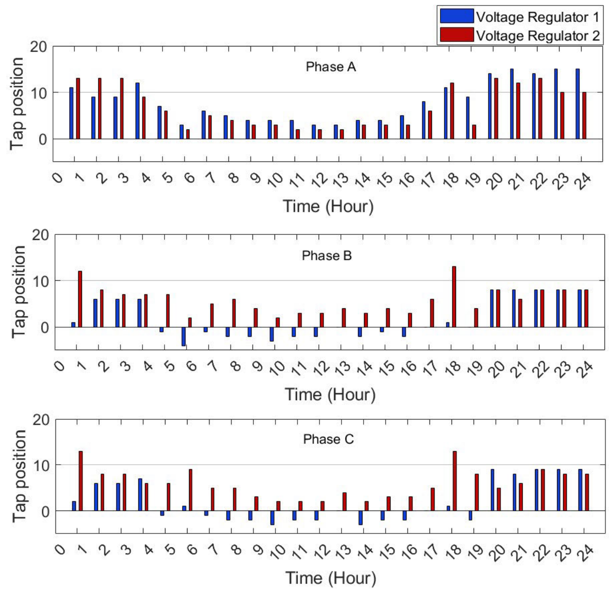

FIGURE 9. Tap positions of voltage regulators- Case 2.

distribution system voltage regulation problem. Therefore, during these times, the changes in tap positions are relatively high compared to the times when there is enough PV generation to solve the voltage deviation problem.

1) SENSITIVITY ANALYSIS

In this part, a sensitivity analysis is developed to evaluate the effect of PV penetration level, which is one of the most important parameters in this study. PV penetration level refers to the amount of PV active power dispatch in the system and in a certain amount of load; any change in PV active power dispatch will affect the crucial parameters of the system, including voltage magnitudes. Therefore, two scaling factors are considered for PV penetration as 0.8 and 1.2 as multiplier coefficients of PV values in the base case. After solving the optimization problem, the values of the objective function, which is the sum of voltage deviations, are obtained. Table 3 provides the results of the sensitivity analysis. As can be observed, the scaling factor 1, which is the base value of PV in case 2, has the lowest value of the objective function. This means that every change in the amount of PV penetration should be analyzed carefully since it can worsen the system voltage profile.

C. CASE 3

This case provides a comprehensive multi-objective study of the operational problem of the aforementioned unbalanced distribution network. Similar to the previous case, the voltage regulator and the reactive power support from the PV systems are considered. However, in this case, the objective is to simultaneously minimize the voltage deviation from the nominal value and the operating cost. To solve the problem, the ε-constraint method has been applied and the results are presented.

TABLE 2. Improvement of voltage profiles for Case-2.

-	Base case	Optimum case	
Time (h:mm)	# of Under-voltages	# of Under-voltages	# of Over-voltages
1:00	Phase A/B/C: 17/2/2	-	-
2:00	Phase A/B/C: 17/2/2	-	-
3:00	Phase A/B/C: 16/0/0	-	-
4:00	Phase A/B/C: 13/0/0	-	-
5:00	Phase A/B/C: 13/0/0	-	-
6:00	Phase A/B/C: 13/0/0	-	-
7:00	Phase A/B/C: 17/0/0	-	-
8:00	Phase A/B/C: 17/3/-	-	-
9:00	Phase A/B/C: 17/11/8	-	-
10:00	Phase A/B/C: 19/11/9	-	-
11:00	Phase A/B/C: 21/11/10	-	-
12:00	Phase A/B/C: 17/11/7	-	-
13:00	Phase A/B/C: 17/11/8	-	-
14:00	Phase A/B/C: 20/11/10	-	-
15:00	Phase A/B/C: 21/11/10	-	-
16:00	Phase A/B/C: 21/11/10	-	-
17:00	Phase A/B/C: 21/11/10	-	-
18:00	Phase A/B/C: 21/11/10	-	-
19:00	Phase A/B/C: 21/11/10	Phase A/B/C: 2/1/2	-
20:00	Phase A/B/C: 21/11/10	Phase A/B/C: 2/1/1	-
21:00	Phase A/B/C: 21/11/10	Phase A/B/C: 2/1/1	-
22:00	Phase A/B/C: 15/11/7	Phase A/B/C: 2/1/1	Phase A/B/C: 1/0/1
23:00	Phase A/B/C: 15/8/-	Phase A/B/C: 1/0/1	Phase A/B/C: 1/0/1
24:00	Phase A/B/C: 15/8/-	Phase A/B/C: 1/0/1	Phase A/B/C: 1/0/1
TVV	728	27	
TVD	6.1940	3.4480	

TABLE 3. Total sum of voltage deviations from the rated value for different scaling factors of PV penetration.

Scaling factor	Value of objective function
0.8	3.7284
1	3.4480
1.2	3.5374

Table 4 shows the values of each objective function for the defined ε value for different hours after eliminating the dominated results. Each step in this table refers to a pre-defined value of ε. It is worth noting that since the higher amounts of PV generation are the main cause of conflict between the two objective functions, only the hours with high PV generation rates are considered in the simulation. In other words, the critical period for decision making supposed to be between 09:00 and 15:00. As can be seen from the table, the two objective functions are in conflict with each other at each hour, and when one is increased, the other decreases. Note that each step refers to an operation strategy in which "Vol. Dev." refers to the sum of voltage deviations calculated by equation (8) and "Cost ($)" refers to the operation cost calculated by equation (11). For instance, in step 1 at 12:00 pm, the value of the first objective function, the sum of voltage deviations from the rated flat value, is 0.1292. This amount is greater than the related values in steps 2 and 3 at the same hour. This is because as we move from step 1 to step 3, the operation cost of the system is allowed to take higher values, and thus the conflict between the objective functions becomes smoother. Furthermore, the sum of voltage deviations can take lower values. In order to present the optimal Pareto set in more detail, Fig. 10 is provided. Each subplot in this figure refers to the Pareto front for each hour between 9-15 pm after eliminating the dominated answers. As can be observed from this figure, the two objective functions are conflicting. Note that OF1 refers to the sum of voltage deviations, and OF2 refers to the total operation cost. This table and figure provide the DSO with a comprehensive

TABLE 4. Values of the objective functions by solving the multi-objective problem for various ε.

Time (h:mm)	OF	Step 1	Step 2	Step 3
9:00	Vol. Dev. Cost ($)	0.1024 9609	0.0976 10416	0.0864 10893
10:00	Vol. Dev. Cost ($)	0.1108 7274	0.0869 7962	0.0817 11051
11:00	Vol. Dev. Cost ($)	0.1219 6660	0.1211 10469	0.0956 11455
12:00	Vol. Dev. Cost ($)	0.1292 5734	0.0729 5987	0.0591 8179
13:00	Vol. Dev. Cost ($)	0.1182 5281	0.1176 7407	0.084 7685
14:00	Vol. Dev. Cost ($)	0.1056 5515	0.0812 6247	0.0775 10003
15:00	Vol. Dev. Cost ($)	0.0847 7943	0.0819 9664	0.0552 11537

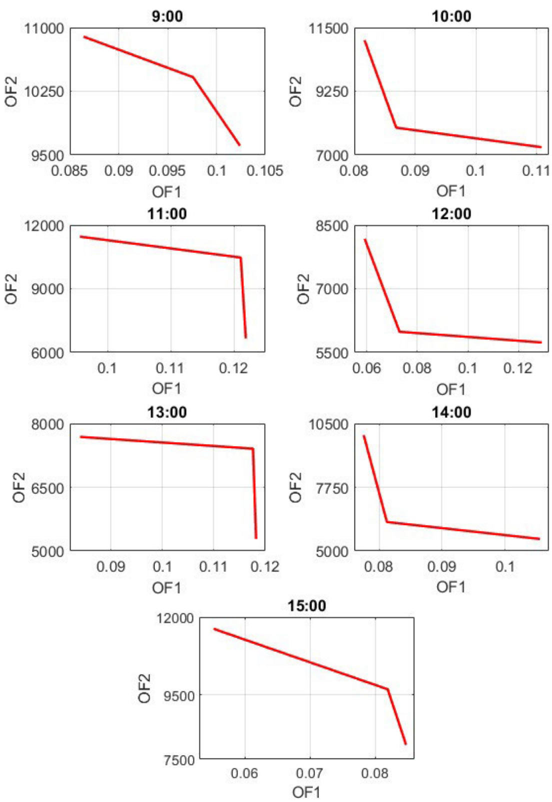

FIGURE 10. Hourly Pareto profile.

overview of the decision-making process when operating the unbalanced distribution network.

For a given hour, i.e., noon, the active and reactive power transactions and the tap positions are illustrated in Fig. 11 and Fig. 12, respectively. As shown in Fig. 11, the active power injection of PV into the distribution grid decreases from the first ε to the last (step 1 to step 3). This behavior is because, given the conflict between the two objective functions,

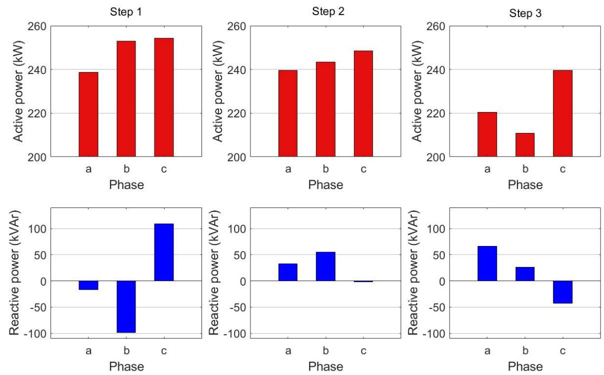

FIGURE 11. Active and reactive power transactions of PV unit at 12 p.m.- Case 3.

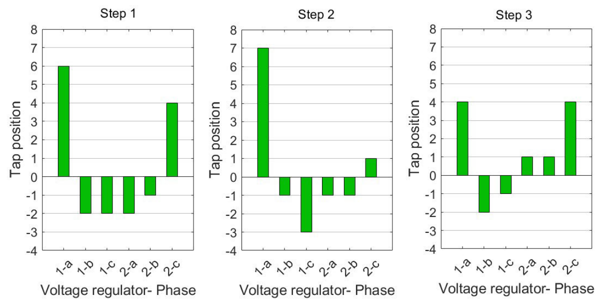

FIGURE 12. Tap positions of voltage regulator at 12 p.m.- Case 3.

while the objective is to minimize the voltage deviation, the operating cost tends to increase. Moving from the first ε to the last, the operating cost can reach higher values, and the main objective, minimizing the voltage deviation, has enough space to decrease. Since the PV operating cost is nearly zero, less PV active power is injected into the system. In addition, reactive power is absorbed from the phases that encounter over-voltage and is injected into the phases which have under-voltage issues. In Fig. 12, since there are two voltage regulators in the system, the indices are shown by 1 and 2 for three phases a,b and c. As can be understood from the figure, the tap positions are set in positive values for the phases that have under-voltage problems and negative values for the phases that experience over-voltage. Note that voltage regulators and PV units are connected in different nodes. Finally, the total main grid energy supply cost is the lowest in the operation condition provided by step 1. Total cost for step 1 is $48016 which is lower than the related value in case 2 with $76551.

The voltage profile of the system for 12pm is shown in Fig. 13. Compared to the base case, where there was no voltage regulation strategy, the voltage profile has improved and is close to the nominal value of 1 p.u. However, there are some voltage violations on bus 890. The reason for these violations is that the mentioned bus is an end node of the feeder, and in some cases, the DSO wants to minimize the cost by sacrificing the voltage in critical situations. Comparative results of the total number of voltage violations

TABLE 5. Improvement of voltage profiles for Case-3.

-	Base case	Optimum case	
Time (h:mm)	# of Under-voltages	# of Under-voltages	# of Over-voltages
9:00	Phase A/B/C: 17/11/8	-	-
10:00	Phase A/B/C: 19/11/9	Phase B, $\varepsilon3$: 1	-
11:00	Phase A/B/C: 21/11/10	-	-
12:00	Phase A/B/C: 17/11/7	Phase B, $\varepsilon1$: 2	Phase C, $\varepsilon1$: 1
13:00	Phase A/B/C: 17/11/8	-	Phase B, $\varepsilon3$: 1
14:00	Phase A/B/C: 20/11/10	Phase B, $\varepsilon3$: 1 & Phase C, $\varepsilon3$: 1	-
15:00	Phase A/B/C: 21/11/10	-	Phase C, $\varepsilon1$: 1
TVV	271	$\varepsilon1$: 2, $\varepsilon2$: 0, $\varepsilon3$: 3	
TVD	2.5277	0.5392	

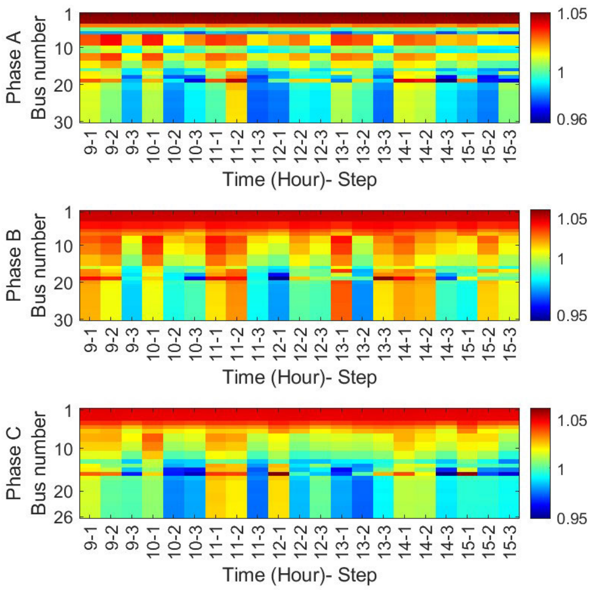

FIGURE 13. Voltage profile of the system- Case 3.

and the objective functions for Case 1 and Case 3 are reported in Table 5. The results show that 269, 271, and 268 of 271 under-voltage violations are eliminated for $\varepsilon1$, $\varepsilon2$, and $\varepsilon3$ operation conditions, respectively, by optimizing the tap-changer positions and PV reactive power outputs. Note that there are a few unavoidable over-voltage violations due to high solar irradiation during the noon time. While using the ε-constraint method, the operation condition related to step 3 is the case that there is the lowest voltage deviation. Therefore, the sum of voltage deviation between hours 9:00 and 15:00 is 0.5395 which is less than 2.5277 in the base case.

IV. CONCLUSION

In this paper, a multi-criteria decision making framework in the optimal operation problem of the modified IEEE 34-bus unbalanced distribution network was presented. In the studied system, a PV unit as well as two tap changer voltage regulators were taken into account. The presented framework was a multi-objective optimization problem that considers the voltage deviation from the rated value and the operation cost as the objective functions. The reactive power support from the PV system was considered along with the tap positions of the voltage regulators as the arms of the proposed voltage control scheme. The EPF method was taken into account for solving the optimization problem and the ε-constraint method was utilized as an efficient approach to deal with the resulting multi-objective optimization scheme.

Three case studies were presented, including the base case, i.e., the operation of the distribution system without any voltage control method to provide a baseline for comparison of the results. In the next case, a voltage control method was implemented on the mentioned system by the reactive power support from the PV with a constant active power injection and adjusting the tap positions of the voltage regulators. Simulation results, in this case, proved that the proposed voltage control method can contribute efficiently to improving the existing under-voltage problem of the system. However, surplus PV active power resulted in the over-voltage issue in the network. For solving all of the above-mentioned problems at once, the final case study was presented. In this case, a multi-objective optimization scheme was presented to minimize the voltage deviation from the rated flat value and the operation cost of the distribution network, simultaneously. Similar to the previous case, reactive power support of PV and voltage regulators was controlling the voltage deviation; however, the PV active power was not constant, providing the DSO with the flexibility to decide about the amount of PV integration. The simulation results on the IEEE 34-bus test system confirmed the ability of the presented model to minimize both of the objective functions and provide the DSO with a comprehensive vision for decision-making in the operation of the distribution networks.

In summary, the results of all the studied cases illustrated the efficiency of the EPF method in solving the optimal operation problem of the distribution network as well as the proper capability of the ε-constraint approach in dealing with the multi-objective optimization scheme. Simulation results revealed that by implementing the presented voltage control method considering the objective as minimizing the voltage deviations from the rated value, there will be a 44.3% decrease in the sum of voltage deviations compared to the case with no voltage control scheme. Moreover, implementing the multi-objective optimization framework, considering the minimization of voltage deviations and operation cost simultaneously, will result in a comprehensive decision-making strategy for the DSO during the critical operation period. In other words, between the hours 9:00 and 15:00, the DSO can consider a 69.4% decrease in the sum of voltage deviations if it accepts a 37.2% decrement in the operation cost or 73.9% decrease in the sum of voltage deviations if it accepts 24.0% decrement in the operation cost or 78.6% decrease in the sum of voltage deviations if it accepts 7.5% decrement in the operation cost. In future studies, the presented model can be expanded by considering the uncertainty of PV power output and comparing the presented solution method with the candidate competitors. In addition, energy storage systems are considered effective complementary equipment for the PV plants that can provide efficient operation of these units. As another research direction, integrating the energy storage system to the studied network can be evaluated in the future.

REFERENCES

[1] Y. Song, Y. Zheng, T. Liu, S. Lei, and D. J. Hill, "A new formulation of distribution network reconfiguration for reducing the voltage volatility induced by distributed generation," *IEEE Trans. Power Syst.*, vol. 35, no. 1, pp. 496–507, Jan. 2020.

[2] O. Ceylan, M. E. Sezgin, M. Göl, M. Verga, R. Lazzari, M. P. Kwaye, and C. Sandroni, "Harmony search algorithm based management of distributed energy resources and storage systems in microgrids," *Appl. Sci.*, vol. 10, no. 9, p. 3252, May 2020.

[3] (2022). *IEA (2022), Renewables 2022, IEA, Paris*. [Online]. Available: https://www.iea.org/reports/renewables-2022

[4] F. Shewarega, I. Erlich, and J. L. Rueda, "Impact of large offshore wind farms on power system transient stability," in *Proc. IEEE/PES Power Syst. Conf. Exposit.*, Mar. 2009, pp. 1–8.

[5] J. C. Boemer, M. Gibescu, and W. L. Kling, "Dynamic models for transient stability analysis of transmission and distribution systems with distributed generation: An overview," in *Proc. IEEE Bucharest PowerTech*, Jun. 2009, pp. 1–8.

[6] Y. Liu, J. Bebic, B. Kroposki, J. de Bedout, and W. Ren, "Distribution system voltage performance analysis for high-penetration Pv," in *Proc. IEEE Energy Conf.*, 2008, pp. 1–8.

[7] D. Mak and D.-H. Choi, "Smart home energy management in unbalanced active distribution networks considering reactive power dispatch and voltage control," *IEEE Access*, vol. 7, pp. 149711–149723, 2019.

[8] T. Aziz and N. Ketjoy, "Enhancing PV penetration in LV networks using reactive power control and on load tap changer with existing transformers," *IEEE Access*, vol. 6, pp. 2683–2691, 2018.

[9] O. Ceylan, A. Dimitrovski, M. Starke, and K. Tomsovic, "A novel approach for voltage control in electrical power distribution systems," in *Proc. IEEE Power Energy Soc. Gen. Meeting (PESGM)*, Aug. 2018, pp. 1–5.

[10] Z. Tang, D. J. Hill, and T. Liu, "Distributed coordinated reactive power control for voltage regulation in distribution networks," *IEEE Trans. Smart Grid*, vol. 12, no. 1, pp. 312–323, Jan. 2021.

[11] C. A. Peñuela Meneses and J. R. S. Mantovani, "Improving the grid operation and reliability cost of distribution systems with dispersed generation," *IEEE Trans. Power Syst.*, vol. 28, no. 3, pp. 2485–2496, Aug. 2013.

[12] K.-Y. Jo, S.-J. Ahn, S.-Y. Yun, and J.-H. Choi, "Efficient day-ahead scheduling voltage control scheme of ULTC and var of distributed generation in distribution system," *IEEE Access*, vol. 9, pp. 157222–157235, 2021.

[13] D. Li, S. Yang, W. Huang, J. He, Z. Yuan, and J. Yu, "Optimal planning method for power system line impedance based on a comprehensive stability margin," *IEEE Access*, vol. 9, pp. 56264–56276, 2021.

[14] A. Mansour-Saatloo, R. Ebadi, M. A. Mirzaei, K. Zare, B. Mohammadi-Ivatloo, M. Marzband, and A. Anvari-Moghaddam, "Multi-objective IGDT-based scheduling of low-carbon multi-energy microgrids integrated with hydrogen refueling stations and electric vehicle parking lots," *Sustain. Cities Soc.*, vol. 74, Nov. 2021, Art. no. 103197.

[15] D. F. Teshome, W. Xu, P. Bagheri, A. Nassif, and Y. Zhou, "A reactive power control scheme for DER-caused voltage rise mitigation in secondary systems," *IEEE Trans. Sustain. Energy*, vol. 10, no. 4, pp. 1684–1695, Oct. 2019.

[16] M. Bell, F. Berkel, and S. Liu, "Real-time distributed control of low-voltage grids with dynamic optimal power dispatch of renewable energy sources," *IEEE Trans. Sustain. Energy*, vol. 10, no. 1, pp. 417–425, Jan. 2019.

[17] S. Magnússon, G. Qu, and N. Li, "Distributed optimal voltage control with asynchronous and delayed communication," *IEEE Trans. Smart Grid*, vol. 11, no. 4, pp. 3469–3482, Jul. 2020.

[18] P. Li, C. Zhang, Z. Wu, Y. Xu, M. Hu, and Z. Dong, "Distributed adaptive robust voltage/VAR control with network partition in active distribution networks," *IEEE Trans. Smart Grid*, vol. 11, no. 3, pp. 2245–2256, May 2020.

[19] R. Cheng, Z. Wang, Y. Guo, and Q. Zhang, "Online voltage control for unbalanced distribution networks using projected Newton method," *IEEE Trans. Power Syst.*, vol. 37, no. 6, pp. 4747–4760, Nov. 2022.

[20] S. Nowak, L. Wang, and M. S. Metcalfe, "Two-level centralized and local voltage control in distribution systems mitigating effects of highly intermittent renewable generation," *Int. J. Electr. Power Energy Syst.*, vol. 119, Jul. 2020, Art. no. 105858.

[21] R. Ebadi, H. Šenyüz, F. Aboshady, O. Ceylan, I. Pisica, and A. Ozdemir, "Voltage control of unbalanced distribution systems with penetration of renewable sources: A gradient-based optimization approach," in *Proc. 57th Int. Universities Power Eng. Conf. (UPEC)*, Aug. 2022, pp. 1–7.

[22] O. Ceylan, S. Paudyal, and I. Pisica, "Nodal sensitivity-based smart inverter control for voltage regulation in distribution feeder," *IEEE J. Photovolt.*, vol. 11, no. 4, pp. 1105–1113, Jul. 2021.

[23] M. F. Ishraque, A. Rahman, S. A. Shezan, and S. M. Muyeen, "Grid connected microgrid optimization and control for a coastal island in the Indian ocean," *Sustainability*, vol. 14, no. 24, p. 16697, Dec. 2022.

[24] S. K. Sarker, S. R. Fahim, N. Sarker, K. Z. Tayef, A. B. Siddique, D. Datta, M. A. P. Mahmud, Md. F. Ishraque, S. K. Das, M. R. I. Sarker, S. A. Shezan, and Z. Rahman, "Ancillary voltage control design for adaptive tracking performance of microgrid coupled with industrial loads," *IEEE Access*, vol. 9, pp. 143690–143706, 2021.

[25] S. A. Shezan, I. Kamwa, M. F. Ishraque, S. M. Muyeen, K. N. Hasan, R. Saidur, S. M. Rizvi, M. Shafiullah, and F. A. Al-Sulaiman, "Evaluation of different optimization techniques and control strategies of hybrid microgrid: A review," *Energies*, vol. 16, no. 4, p. 1792, Feb. 2023.

[26] A. F. Güven and M. M. Samy, "Performance analysis of autonomous green energy system based on multi and hybrid metaheuristic optimization approaches," *Energy Convers. Manage.*, vol. 269, Oct. 2022, Art. no. 116058.

[27] D. Cao, J. Zhao, W. Hu, F. Ding, N. Yu, Q. Huang, and Z. Chen, "Model-free voltage control of active distribution system with PVs using surrogate model-based deep reinforcement learning," *Appl. Energy*, vol. 306, Jan. 2022, Art. no. 117982.

[28] D. Cao, J. Zhao, W. Hu, N. Yu, F. Ding, Q. Huang, and Z. Chen, "Deep reinforcement learning enabled physical-model-free two-timescale voltage control method for active distribution systems," *IEEE Trans. Smart Grid*, vol. 13, no. 1, pp. 149–165, Jan. 2022.

[29] R. Aboli, M. Ramezani, and H. Falaghi, "A hybrid robust distributed model for short-term operation of multi-microgrid distribution networks," *Electric Power Syst. Res.*, vol. 177, Dec. 2019, Art. no. 106011.

[30] J. Radosavljevic, M. Jevtic, D. Klimenta, and N. Arsic, "Optimal power flow for distribution networks with distributed generation," *Serbian J. Electr. Eng.*, vol. 12, no. 2, pp. 145–170, 2015.

[31] M. Nick, R. Cherkaoui, and M. Paolone, "Optimal allocation of dispersed energy storage systems in active distribution networks for energy balance and grid support," *IEEE Trans. Power Syst.*, vol. 29, no. 5, pp. 2300–2310, Sep. 2014.
[32] B. Ahmadi, O. Ceylan, and A. Ozdemir, "Distributed energy resource allocation using multi-objective grasshopper optimization algorithm," *Electric Power Syst. Res.*, vol. 201, Dec. 2021, Art. no. 107564.
[33] V. Sarfi and H. Livani, "Optimal volt/VAR control in distribution systems with prosumer DERs," *Electric Power Syst. Res.*, vol. 188, Nov. 2020, Art. no. 106520.
[34] R. Ebadi, A. S. Yazdankhah, B. Mohammadi-Ivatloo, and R. Kazemzadeh, "Coordinated power and train transportation system with transportable battery-based energy storage and demand response: A multi-objective stochastic approach," *J. Cleaner Prod.*, vol. 275, Dec. 2020, Art. no. 123923.
[35] E. Davoodi, E. Babaei, B. Mohammadi-Ivatloo, M. Shafie-Khah, and J. P. S. Catalão, "Multiobjective optimal power flow using a semidefinite programming-based model," *IEEE Syst. J.*, vol. 15, no. 1, pp. 158–169, Mar. 2021.
[36] F. Sánchez and F. Gonzalez-Longatt, "Optimization of frequency controller parameters of a Bess by considering rate of change constraints," in *Proc. IEEE Milan PowerTech*, 2019, pp. 1–6.
[37] S. Singh, P. Chauhan, and N. Singh, "Capacity optimization of grid connected solar/fuel cell energy system using hybrid ABC-PSO algorithm," *Int. J. Hydrogen Energy*, vol. 45, no. 16, pp. 10070–10088, Mar. 2020.
[38] Q. Zhang, K. Dehghanpour, and Z. Wang, "Distributed CVR in unbalanced distribution systems with PV penetration," *IEEE Trans. Smart Grid*, vol. 10, no. 5, pp. 5308–5319, Sep. 2019.
[39] A. F. Güven, N. Yörükeren, E. Tag-Eldin, and M. M. Samy, "Multi-objective optimization of an islanded green energy system utilizing sophisticated hybrid metaheuristic approach," *IEEE Access*, vol. 11, pp. 103044–103068, 2023.
[40] Q. Zhang, Y. Guo, Z. Wang, and F. Bu, "Distributed optimal conservation voltage reduction in integrated primary-secondary distribution systems," *IEEE Trans. Smart Grid*, vol. 12, no. 5, pp. 3889–3900, Sep. 2021.
[41] Q. Zhang, F. Bu, Y. Guo, and Z. Wang, "Tractable data enriched distributionally robust chance-constrained conservation voltage reduction," *IEEE Trans. Power Syst.*, vol. 39, no. 1, pp. 1–15, 2024.
[42] S. Y. Derakhshandeh, R. Pourbagher, and A. Kargar, "A novel fuzzy logic Levenberg–Marquardt method to solve the ill-conditioned power flow problem," *Int. J. Electr. Power Energy Syst.*, vol. 99, pp. 299–308, Jul. 2018.
[43] M. Huneault and F. D. Galiana, "A survey of the optimal power flow literature," *IEEE Trans. Power Syst.*, vol. 6, no. 2, pp. 762–770, May 1991.
[44] C. S. Cheng and D. Shirmohammadi, "A three-phase power flow method for real-time distribution system analysis," *IEEE Trans. Power Syst.*, vol. 10, no. 2, pp. 671–679, May 1995.
[45] P. Venkataraman, *Applied Optimization With MATLAB Programming*. Hoboken, NJ, USA: Wiley, 2009.
[46] G. Mavrotas, "Effective implementation of the ε-constraint method in multi-objective mathematical programming problems," *Appl. Math. Comput.*, vol. 213, no. 2, pp. 455–465, Jul. 2009.
[47] H. A. Taha, M. H. Alham, and H. K. M. Youssef, "Multi-objective optimization for optimal allocation and coordination of wind and solar DGs, BESSs and capacitors in presence of demand response," *IEEE Access*, vol. 10, pp. 16225–16241, 2022.
[48] B. A. Robbins, H. Zhu, and A. D. Domínguez-García, "Optimal tap setting of voltage regulation transformers in unbalanced distribution systems," *IEEE Trans. Power Syst.*, vol. 31, no. 1, pp. 256–267, Jan. 2016.
[49] W. H. Kersting, "The modeling and application of step voltage regulators," in *Proc. IEEE/PES Power Syst. Conf. Exposit.*, Mar. 2009, pp. 1–8.
[50] *IEEE Standard for Interconnection and Interoperability of Distributed Energy Resources With Associated Electric Power Systems Interfaces*, IEEE Standard 1547-2018, 2018, pp. 1–138.
[51] C. Grigg, P. Wong, and F. Alvarado, "The IEEE 34-bus test system," *IEEE Trans. Power App. Syst.*, vol. PAS-96, no. 2, pp. 938–945, Jul. 1977.
[52] S. Pfenninger and I. Staffell, "Long-term patterns of European PV output using 30 years of validated hourly reanalysis and satellite data," *Energy*, vol. 114, pp. 1251–1265, Nov. 2016.
[53] EPIAS. *EPIAS Transparency Platform*. Accessed: Nov. 4, 2020. [Online]. Available: https://seffaflik.epias.com.tr/transparency/index.xhtml

RAMIN EBADI received the B.Sc. degree in electrical engineering (power systems) from the University of Tabriz, Tabriz, Iran, in 2017, and the M.Sc. degree in electrical engineering (power systems) from Sahand University of Technology, Sahand New Town Campus, Iran, in 2020. He is currently with İstanbul Technical University, İstanbul, Turkey. His research interests include techno-economic analysis of renewable integrated power systems, decision-making under uncertainty, distributed energy resources, and optimization techniques.

F. M. ABOSHADY (Senior Member, IEEE) received the B.Sc. and M.Sc. degrees in electrical engineering from Tanta University, Egypt, in 2010 and 2014, respectively, and the Ph.D. degree in electrical and electronic engineering from the University of Nottingham, U.K., in 2019. He is currently a Research Fellow with Brunel University London and an Assistant Professor with Tanta University. His research interests include fault location strategies, protection of electric grids, electric vehicles, and integration of renewable energy systems.

OGUZHAN CEYLAN (Member, IEEE) received the M.Sc. and Ph.D. degrees in computational science and engineering from İstanbul Technical University, İstanbul, Turkey, in 2003 and 2012, respectively. From 2013 to 2015, he was a Postdoctoral Researcher with the University of Tennessee, Knoxville, TN, USA. He is currently an Associate Professor with the Management Information Systems Department, Kadir Has University. His research interests include smart grids, integration of renewable into distribution systems, and intelligent optimization methods.

IOANA PISICA (Senior Member, IEEE) is currently an Associate Professor of power systems and a member of the Brunel Interdisciplinary Power Systems Research Centre, Brunel University London. She has been involved in agent-based modeling, smart metering communications, and analysis of large amounts of data from smart meters, with the aim to achieve energy efficiency. Her research interests include power systems operation optimization, renewable energy systems, power quality, and energy efficiency in the built environment and industry. Her expertise in building management systems and energy management systems spans across more than 12 years.

AYDOGAN OZDEMIR (Senior Member, IEEE) was born in Artvin, Turkey, in January 1957. He received the B.Sc., M.Sc., and Ph.D. degrees in electrical engineering from İstanbul Technical University, İstanbul, Turkey, in 1980, 1982, and 1990, respectively. After 40 years of academic life at İstanbul Technical University, he joined Kadir Has University, İstanbul. His current research interests include high voltage engineering and electric power systems, with an emphasis on reliability assessment, distributed generation, and intelligent system applications in electric power systems.