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Probabilistic multi-objective arbitrage of dispersed energy storage systems for optimal congestion management of active distribution networks including solar/wind/CHP hybrid energy system

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Nowadays, dispersed storage systems (DSSs) have an irrefutable role in creating the favourable substrates for optimal management of active distribution networks (ADNs). Actually, they are capable of managing the congestion of ADNs by providing feasible solution that can dramatically improve the system reliability and resiliency against contingencies that threaten the network security. To this end, this paper deals with optimal arbitrage of DSSs in ADNs including the solar/wind/CHP hybrid energy system aiming at finding the optimal trade-off between congestion and economic targets by defining a novel probabilistic risk-based multi-objective model. In particular, the proposed method is fulfilled considering (1) feeders/line congestions, (2) network voltage deviations, (3) power losses, (4) operating cost of distributed generation associated with the cost of DSS charging/discharging, and (5) uncertainty pertaining to renewable generation. The two conflicting objectives consisting of congestion alleviation and procurement cost minimization are optimized simultaneously by multiobjective particle swarm optimization to purvey the Pareto-optimal curve, and subsequently, fuzzy decision-making is executed to extract the best solution from the Pareto curve obtained with respect to defined risk-based strategies. Finally, a case study referring to the modified IEEE 33-bus distribution system is utilized to evidence the efficiency and proficiency of the proposed congestion relief approach. *Published by AIP Publishing.* https://doi.org/10.1063/1.5035081

NOMENCLATURE

Sets and indices

b	Index for BES units.
c	Index for CHP units.
i	Index for network busses.
l	Index for network lines.
m	Index for PV units.
n	Index for WT units.
N_{BES}	Set of BES units.
N_{bus}	Set of busses.
N_{CHP}	Set of CHP units.
N_l	Set of lines.
N_{PV}	Set of PV units.
N_{WT}	Set of WT units.
t	Index for hour.

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Variables

$g(t)$	Global best position of particle i in generation t.
$H_i(x)$	Membership function.
$P_i(t)$	Personal best position of particle i in generation t.
$P_{b,t}^{ch}$	charged power of bth BES at time t.
$P_{b,t}^{dis}$	Discharged power of bth BES at time t.
P_i^{net}	Net injected active power in the ith bus.
$P_{m,t}^{\mathrm{pv}}$	Generated power of the mth PV in time t.
$P_{n,t}^{\mathrm{wind}}$	Generated power of the nth WT in time t.
P_t^{DG}	DG power production at time t.
P_t^{load}	Power load at time t.
P_t^{REST}	Rest of power in the power balance equation at time t.
$P_{t,l}$	Active power flow of line l at time t.
$P_{t,l}^{cap}$	Maximum capacity of line l at time t.
$P_{t,l}^{loss}$	Power losses of line l at time t.
Q_i^{net}	Net injected reactive power in the ith bus.
$SoC_{b,t}$	State of charge of bth BES at time t.
V_i	Voltage magnitude of bus i.
$V_i(t)$	Velocity of particle i in generation t.
$X_i(t)$	Position of particle i in generation t.
Y_l	Admittance of line l.
δ_i	Voltage angle of node i.
θ_l	Admittance angle of line l.

Parameters

C	Scale factor of the Weibull PDF.
c_1, c_2	Acceleration coefficients.
G	Global solar radiation.
$G_{\mathrm{ING}}, G_{\mathrm{STG}}$	Solar irradiance in standard and study conditions.
iter	Iteration number of the optimization algorithm.
$\mathrm{iter}_{\max}$	Maximum iteration number.
k	Power temperature factor.
K^{DG}	Operating coefficient of DG.
K^{ESS}	Operating coefficient of BES.
L	Number of non-dominated solutions.
NOCT	Normal operating cell temperature of PV.
P_{STG}	Rated output power by the module under standard test conditions.
P_i^{rat}	rated power of the WT installed in bus i.
$P^{\min}, P^{\max}$	Minimum and maximum active powers of DGs.
$Q^{\min}, Q^{\max}$	Minimum and maximum reactive powers of DGs.
r_1, r_2	Random number in the range of [0,1].
s	Shape factor of the Weibull PDF.
$SoC_b^{\min}$	Minimum state of charge of bth BES.
$SoC_b^{\max}$	Maximum state of charge of bth BES.
T_a	Ambient temperature.
T_C, T_{ref}	Cell and air temperature of PV units.
$V^{\min}, V^{\max}$	Minimum and maximum ranges of voltage magnitude.
$w_{\min}, w_{\max}$	Minimum and maximum weights.
x, γ	Beta function parameter.
Z_i, z_i	Maximum and minimum values of the ith objective function.
η_{ch}	Charging efficiency of BES.
η_{dis}	Discharging efficiency of BES.

v	Wind speed of the farm under study.
$v_{\mathrm{c\,in}}$	Cut-in speed.
$v_{\mathrm{c\,out}}$	Cut-out speed.
v_{rat}	Rate speed of the WT.
Π_t^{ch}	BES charging price at time t.
Π_t^{dis}	BES discharging price at time t.
$\upsilon_{\max}, \upsilon_{\min}$	Initial and final velocities.
ω	Inertia weight of the particle.

I. INTRODUCTION

A. Concepts and motivations

With a progressive increase in electricity demand in recent years and to avoid environmental pollution, it is necessary to install a large number of distributed generations (DGs) such as solar panels, wind turbines (WTs), and combined heat and power (CHP) units in the active distributed network (ADN). The increase in DG penetration causes a number of technical problems such as overvoltage, congestion in lines, and harmonics, and the increasing demand causes lack of generation capacity, blackouts, rising electricity prices, etc.[1] The continued increase in demand leads to extra costs for the construction of new power stations and system feeders so that these costs are only for providing electricity in some exigent times of year.[2] Hence, appropriate methods must be taken into account in order to release the capacity of lines and thereby to relieve the congestion of the network in other periods (i.e., peak periods).

Congestion is defined as a situation of overloading of network lines or transformers which causes lack of coordination between generation and consumption or as a result of unexpected contingencies such as sudden increase in load demand or failure of equipment, which in turn prevents the new contracts and infeasibility in existing contracts and additional outages.[3] Also, the congestion causes excessive flow of current and creates thermal stress on distribution cables. Therefore, it is necessary to use the methods such as dispersed storage systems (DSSs) to reduce the consumption at peak times (peak shaving) or shifting dispensable loads to other periods (off-peak hours) which could reduce the congestion of lines.

In peak periods, the systems usually operate close to their maximum capacity, and so, the security margin of the network decreases significantly. Due to constraints on the distribution system, a limited amount of power can be transferred between two locations in the power grid.[4] In practice, because of violations of the operating limits such as the power flow and voltage constraints, it is not always possible for all bilateral and multi-lateral contracts to be fully delivered and to provide the total market demand. The congestion should be reduced, in many cases, using the cost-free method, such as network reconfiguration, change transformer tap, and the application of flexible alternative current transmission system (FACTS) devices.[5,6] In other cases, if it is not possible to reduce congestion by cost-free methods, some non-cost-free controller methods, such as re-dispatch of generation and curtailments of loads (load shedding programs), can be used to relieve the congestion of critical lines.

To overcome these mentioned challenges, recently, the focus has been on congestion management (CM), which is an important topic in the distribution system operator (DSO). CM methods are mainly divided into two categories, namely, the preventive and corrective CM methods. Preventive CM methods are based on using the transmission right and available transfer capability (ATC). On the other hand, ATC based methods focus on informing customers to optimally modify their consumption pattern in order to alleviate the congestion and increase their benefits.[7] CM in terms of time is as follows:

(1) Short-term CM
Short-term methods are generally used in the real-time electricity markets and are basically the same corrective methods after the occurrence of network congestion.

(2) Mid-term CM

Medium-term methods are predominantly preventive techniques, the most popular of them is the market of monthly transfer right sales in different types.

(3) Long-term CM

Long-term methods are based on the development of transmission and production and have a perennial horizon.

One of the most popular methods for optimal management of ADNs is the DSS units, which can also mitigate the fluctuations of renewable generation installed on the system. In order to cope with such uncertainties, DSS units have been widely employed recently. With respect to this issue, it can be concluded that in the ADN, utilization of DSS units could make a great impact on power flow in distribution lines, and therefore, it can manage the congestion of the system. In so doing, this paper proposes a novel probabilistic multi-objective model for optimal arbitrage of DSSs in ADNs with an aim to manage the congestion of the system and also can create a trade-off between economic and technical issues of the problem. Moreover, the proposed scheduling model addresses the probabilistic operation of DSSs considering uncertainties subject to solar and wind generations. Several risk-based strategies are suggested to verify the introduced scheduling problem.

B. Literature review

Generally, the CM approaches proposed in the previous literature can be categorized into three basic groups, namely, (i) centralized optimization accompanied by optimal power flow (OPF), (ii) re-dispatch of generators via price signals derived from anticipated market resolution to diagnose the congestion, which is named nodal pricing, and (iii) applying bilateral contracts between the producer and the consumer to reduce the congestion of lines. In Ref. 7, the authors introduced the optimal demand response program for CM to reduce the operation costs and improve the reliability. A review of several methods, which have been proposed for CM, was performed in Ref. 8. In particular, the OPF is the most common method to optimally manage the congestion in the power systems.[9] In Ref. 10, both FACTS device controllers and demand response programs (DRPs) are used to reduce the congestion at a minimum cost. The main objective of Ref. 11 is to provide a method for decreasing the number of generators and optimal rescheduling for their productions and CM in the market at the minimum rescheduling cost. The second objective is to solve the problem of CM by the PSO algorithm. CM is solved with optimal rescheduling of generator production using the fuzzy adaptive bacterial foraging algorithm for the first time in Ref. 12.

Conejo illustrated the effect of voltage stability constraints on reducing congestion.[13] The multiobjective particle swarm optimization (MOPSO) algorithm is discussed for minimizing the cost of CM and overload indicator.[14] The distribution congestion price-based market mechanism is presented in Ref. 15. This article investigated the impact of DRP on CM in ADNs in the next-day electricity market. In Ref. 16, CM is presented by the clustering or zoning approach. In Ref. 17, a general study was conducted on transmission lines with wind energy sources to alleviate congestion. An improved differential evolution algorithm is proposed to solve the problem, which is mentioned in this paper. Reference 18 presented a distributed robust method for reducing congestion in the presence of flexible buildings in the ADN. A plan for charging and discharging battery storage resources, which provides maximum overall benefits to wind power generators and which is solved by dynamic programing, is discussed in Ref. 19. In Ref. 20, a comprehensive study on optimal battery sizing was presented in a microgrid (MG). Critical coefficients such as the wide range of characters for different technologies, distributed development, the effect of charging and discharging depths, and the number of charging and discharging processes on the battery energy storage (BES) and coordination of different modes of operation of MG were discussed. Furthermore, the effect of charging and discharging depths of BES and the frequency on the life of the BES were expressed.

In Ref. 21, a combination of the distributed control scheme for residential battery storage units with photovoltaic (PV) systems is presented. This design is capable of solving the overvoltage problem created through PV systems. In Ref. 22, a plan has been proposed to accommodate BES by combining wind systems. BES will store all energy lost from wind systems and allocate optimal energy storage for minimizing annual electricity costs. Allocation of different kinds of DGs is formulated by the efficient analytical (EA) algorithm which reduces the active power loss arising from DGs. Moreover, this paper presented a combining method as EA-OPF to minimize the power losses.[23] Pareto dominance was used in Ref. 24 by applying the PSO algorithm to allow the algorithm to use the multiple objective functions simultaneously. Unlike other propositions, this algorithm uses a secondary repository of particles.

C. Novelties and contributions

Due to the existence of several dispersed DGs in the ADN which have different prices and productions, it is possible for loads to provide their power from cheaper and more reliable DGs.[25] The load consumption of consumers changes in each hour and includes peak and off-peak periods. In peak periods, more loads connect to the network and consumption increase. Therefore, at these times, some lines of the network will become congested. These congestions which occur on the lines should be managed and alleviated. To solve the congestion problem, existing lines should be expanded, and their available capacity would be increased. However, this solution is not appropriate because the expansion of the ADN imposes high investment costs on the systems.

The recommended solution of this paper to solve the congestion problem is to use the distributed BES resources available in the ADN. So, at off-peak periods, the BESs purchase power from the network with a price lower than DGs and charge. Then, at the peak periods when the price of electricity is high, they can sell the stored power to consumers, which in turn reduces the congestion of critical lines and operation costs. The main purpose of this paper is to minimize the procurement costs and alleviate the congestion of the ADN simultaneously by utilizing distributed BES units which is not investigated until now. In this paper, we discuss the following items:

1. Utilizing distributed BES to manage the congestion of the distribution system and mitigation of sharp fluctuation of solar and wind generations.
2. Multiobjective congestion-cost modeling for the proposed CM problem from the DSO viewpoint.
3. Optimal decentralized energy management of dispatchable and renewable DGs.
4. Handling the uncertainties of renewable generation via applying probabilistic modelling.
5. Proposing different risk-based strategies to capture the minus impacts of sharp fluctuations of renewable generation on the decision making.
6. Formulation of the problem as mixed integer nonlinear programing (MINLP) and using MOPSO algorithms along with fuzzy decision making to minimize both conflicting objectives simultaneously considering various practical constraints.

D. Paper organization

The remainder of this paper is organized as follows: Sec. II presents the formulation of CM and the cost model. Section III provides an overview of the MOPSO algorithm and fuzzy decision theory. Section IV presents problem data and simulation results of the proposed concepts. Finally, a conclusion is drawn in Sec. V.

II. PROBLEM FORMULATION

In the power system application, there are two types of storage devices as follows: (1) low-capacity and fast-response unit in order to mitigate the fast fluctuations in generation or demand and also (2) high capacity and low-response unit to transfer the energy over peak periods into off-peak periods.[26,27] With regard to this issue, this paper proposes BES to manage the congestion of the ADN and to control the uncertainty of the renewable generation. From the technological viewpoint, there are disparate storage devices each of which has some advantages and disadvantages. So, selecting a storage device for a specific application should be done intelligently and based on the features required. For instance, the lead acid batteries have a short lifespan compared to other off-grid equipments. However, because of the low price of acid batteries, they have been placed on top of the battery market. On the other side, the Li-ion batteries have two main advantages, namely, long battery life and low life cycle cost. The comparison between various storage devices is depicted in Fig. 1.

Considering the battery lifespan, the cost per cycle for the Li-ion is lower than that for lead acid. Therefore, with these features, long-term operation of the Li-ion is more cost effective than that of lead acid, even if the upfront cost is higher. Upfront cost is an important parameter in choosing the type of battery. Compared to other technologies, Li-ions are much more suitable because of their capacity and output power. Lithium batteries are lighter and smaller than other rechargeable batteries.[28] In this paper, a Li-ion battery is used as a storage device for CM. In general, the BES is charged and discharged at off peak and peak hours, respectively. To deal with the alternating PV output, BES charging and discharging planning should be organized at least hourly, depending on load variations and intermittent outputs of PV modules. If the interaction between batteries, PV, and loads is detected effectively, battery benefits will be achieved, such as reducing line losses, improving power quality, and improving reliability.

A. Congestion management

1. First objective function

The purpose of congestion management is to reduce congestion or, in other words, reduce the amount of power transmitted from overloaded lines. For this purpose, the difference in power flow and the capacity of the lines should be minimized

$$\min F_1 = \sum_{t=1}^{24} \sum_{l=1}^{N_l} \left(\left| P_{t,l} - P_{t,l}^{cap} \right| \right). \tag{1}$$

The objective of Eq. (1) is to minimize the power flow in the lines of the network, which in turn decreases the congestion of the network and overloading of critical lines.

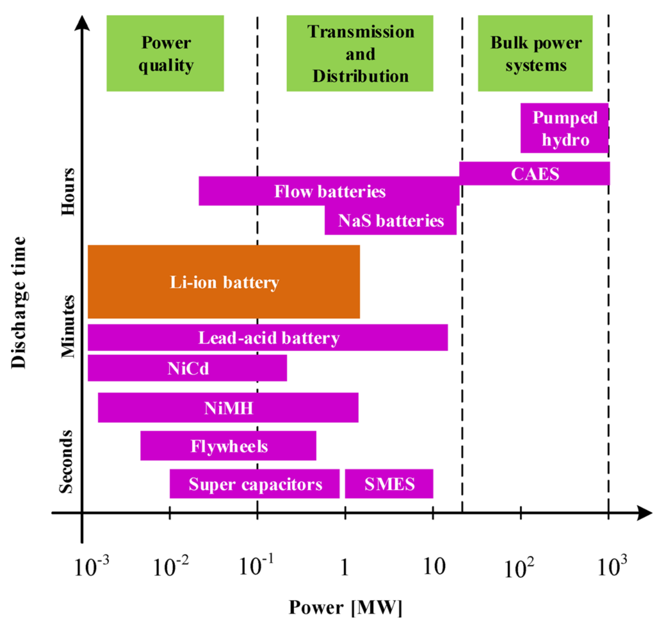

FIG. 1. Characteristics of various energy storages.

2. Constraints

In this paper, the proposed CM approach is implemented considering different practical and technical constraints as presented below

$$P_l^{\min} \leq P_l \leq P_l^{\max}, \quad \forall l \in N_{line}, \tag{2}$$

$$Q_l^{\min} \leq Q_l \leq Q_l^{\max}, \quad \forall l \in N_{line}, \tag{3}$$

$$V_i^{\min} \leq V_i \leq V_i^{\max}, \quad \forall i \in N_{bus}, \tag{4}$$

$$I_l = (V_i \angle \delta_i - V_{i+1} \angle \delta_{i+1})/R + jX, \quad \forall l \in N_l, \quad \forall i \in N_{bus}, \tag{5}$$

$$P_{i+1} - jQ_{i+1} = V_{i+1}^{*} I_l, \quad \forall l \in N_l, \quad \forall i \in N_{bus}, \tag{6}$$

$$\begin{aligned} V_{i+1} = \Big[& \{(P_{i+1}R + Q_{i+1}X - 0.5V_i^2)^2 - (R^2 + X^2)(P_{i+1}^2 + Q_{i+1}^2)\}^{0.5} \\ & -(P_{i+1}R + Q_{i+1}X - 0.5V_i^2)\Big]^{0.5}, \quad \forall i \in N_{bus}, \end{aligned} \tag{7}$$

$$P_{t,l}^{loss} = \mathrm{real}(R(P_{i+1}^2 + Q_{i+1}^2)/V_{i+1}^2), \ \forall t \in T, \tag{8}$$

$$P_{t,l} = \mathrm{real}(V_i \times I_l^{*}), \quad \forall t \in T, \tag{9}$$

$$P_i^{net} = \sum_{l=1}^{N_l} \sum_{i=1}^{N_{\mathrm{bus}}} V_i V_{i+1} Y_l \cos(\delta_i - \delta_{i+1} - \theta_l), \tag{10}$$

$$Q_i^{net} = \sum_{l=1}^{N_l} \sum_{i=1}^{N_{\mathrm{bus}}} V_i V_{i+1} Y_l \sin(\delta_i - \delta_{i+1} - \theta_l). \tag{11}$$

Constraints (2) and (3) denote the minimum and maximum active and reactive powers of the lth line, respectively. Constraint (4) describes the lower and upper limits of voltage in the ith bus. Equation (5) calculates the current of the lth line. Equations (6)–(9) are related to the backward-forward method to calculate the power loss of the lth line in time t. In the following, Eqs. (10) and (11) show the injected active and reactive powers in the ith bus at time t, respectively.

B. Procurement costs

1. Second objective function

According to the equilibrium among generation and consumption and comparison between the market price and the price of power generated by local resources, it is planned to charge and discharge the BES. So, if the amount of DG resources in the network and upstream is higher than the consumption rate and also the cost of the BES charge is less than the price of the electricity market in this case, the BES will act as a load and therefore charges. However, if the amount of DG resources in the network and upstream is lower than the amount of consumption and also the cost of BES discharging is lower than the price of the electricity market, in this case, the BES will enter the network as a source of generation.

$$\min F_2 = \sum_{t=1}^{24} \left[\sum_{b=1}^{N_{\mathrm{BES}}} \left[\begin{aligned} & (K^{PV} \times P_t^{PV}) + (K^{WT} \times P_t^{WT}) + (K^{CHP} \times P_t^{CHP}) \\ & +(\Pi_t^{ch} \times P_{b,t}^{ch}) + (K^{BES} \times P_{b,t}^{ch}) + \sum_{l=1}^{N_l} \left(P_{t,l}^{loss} \times K^{loss} \right) \end{aligned} \right] \right]. \tag{12}$$

Equation (12) shows the operational cost of DG units inserted in the network, including wind turbines (WTs), PV arrays, and CHP units. By optimal charging and discharging of BES and optimal management of DG productions in the 24-h periods, each of the lines that are congested will be managed along with minimum possible cost by this approach.

2. Constraints

Various constraints are considered in the optimization problem, which are shown in the following:

$$P_t^{\mathrm{REST}} = P_t^{\mathrm{load}} - P_t^{DG}, \quad \forall t \in T, \tag{13}$$

$$P_t^{DG} = P_{n,t}^{\mathrm{wind}} + P_{m,t}^{\mathrm{PV}} + P_{c,t}^{\mathrm{CHP}}, \quad \forall t \in T, \tag{14}$$

$$P_{t,n}^{WT,\min} \le P_{t,n}^{WT} \le P_{t,n}^{WT,\max}, \quad \forall n \in N_{WT}, \quad \forall t \in T, \tag{15}$$

$$P_{t,m}^{PV,\min} \le P_{t,m}^{PV} \le P_{t,m}^{PV,\max}, \quad \forall m \in N_{PV}, \quad \forall t \in T, \tag{16}$$

$$P_{t,c}^{CHP,\min} \le P_{t,c}^{CHP} \le P_{t,c}^{CHP,\max}, \quad \forall c \in N_{CHP}, \quad \forall t \in T. \tag{17}$$

Equations (13) and (14) show the total power balance and the total generated power of DG resources at time t, respectively. Moreover, constraints (15)–(17) restrict the prohibited operation zones of DG units.

(a) **BES:** Batteries are made from compact cells that convert chemical energy to electrical energy and vice versa. The voltage and the desired flow level for the batteries are achieved through the parallel and series connection of cells. The batteries are ranked in terms of their power and energy. The efficiency, lifetime, operating temperature, discharging depth (usually, the batteries are not fully discharged and the discharging depth depends on the discharge rate), and the energy density are some of the most important characteristics[29]

$$SoC_{b,t+1} = SoC_{b,t} + (P_{b,t}^{ch}\eta_{ch} - P_{b,t}^{dis}/\eta_{dis}), \quad \forall t \in T, \tag{18}$$

$$SoC_b^{\min} \le SoC_{b,t} \le SoC_b^{\max}, \quad \forall t \in T, \quad \forall b \in N_{\mathrm{BES}}, \tag{19}$$

$$0 \le P_{b,t}^{\mathrm{ch}} \le P_b^{\mathrm{ch,max}}, \quad \forall t \in T, \quad \forall b \in N_{\mathrm{BES}}, \tag{20}$$

$$0 \le P_{b,t}^{dis} \le P_b^{\mathrm{dis,max}}, \quad \forall t \in T, \quad \forall b \in N_{\mathrm{BES}}. \tag{21}$$

Equation (18) denotes the state of charging of the bth battery in time t, and Eqs. (19)–(21) express the state of charging limits and the maximum power of charging/discharging of the bth battery in time t, respectively.

(b) **WT:** The WT production depends mainly on the speed and power of the wind. The Weibull probability density function (PDF) is used to predict the wind speed using the following equation (Refs. 30 and 31):

$$\mathrm{PDF}(v) = \left(\frac{s}{c}\right)\left(\frac{v}{c}\right)^{s-1} \exp\left(-\left(\frac{v}{c}\right)^{s}\right). \tag{22}$$

Equation (22) describes the Weibull probability density function. The generated power of the WT in time t with regard to the wind speed is expressed in Eq. (23). The PDF and Cumulative Distribution Function (CDF) of wind speed are given in Fig. 1 based on the statistical data of the location where WTs are installed

$$P_{n,t}^{\mathrm{wind}}(v) = \begin{cases} P_b^{\mathrm{rat}}; & v_{\mathrm{rat}} \le v \le v_{\mathrm{c\,out}} \\ \dfrac{v - v_{\mathrm{c\,in}}}{v_{\mathrm{rat}} - v_{\mathrm{c\,in}}}; & v_{\mathrm{c\,in}} \le v \le v_{\mathrm{rat}} \\ 0; & v \le v_{\mathrm{c\,in}} \text{ and } v \ge v_{\mathrm{c\,out}}. \end{cases} \tag{23}$$

(c) **PV modules:** PV systems are the direct conversion of sunlight into electricity energy without any greenhouse gas emissions. The PV output depends on the angle and intensity of sunlight. The beta PDF is used to predict the amount of sunlight as shown in Fig. 2

$$\mathrm{PDF}(x) = x^{\gamma-1}(1-x)^{\beta-1}. \tag{24}$$

Equation (24) describes the beta PDF. The generated power of PV modules can be kept in a standalone system, can be stored in BES units, or can feed a greater electricity power grid. The PV power depends on the intensity of sunlight and ambient temperature which could be calculated as follows:

$$P_{m,t}^{\mathrm{pv}} = P_{\mathrm{STG}} \times \frac{G_{\mathrm{ING}}}{G_{\mathrm{STG}}} \times (1 + k(T_{\mathrm{C}} - T_{\mathrm{C,ref}})), \quad \forall t \in T. \tag{25}$$

Equation (25) shows the power output of mth PV in time t, where T_C can be expressed in the following equation:

$$T_C = T_a + \frac{\mathrm{NOCT} - 20}{0.8} \times G. \tag{26}$$

The normal operating cell temperature (NOCT) is defined as the cell temperature when the photovoltaic panel falls below 0.8 Kw/m^2 sunshine and 20 °C of environment temperature. NOCT is usually between 42 and 46 °C. The schematic structure of the hybrid stand-alone PV system and WT connected to ADN is illustrated in Fig. 3.

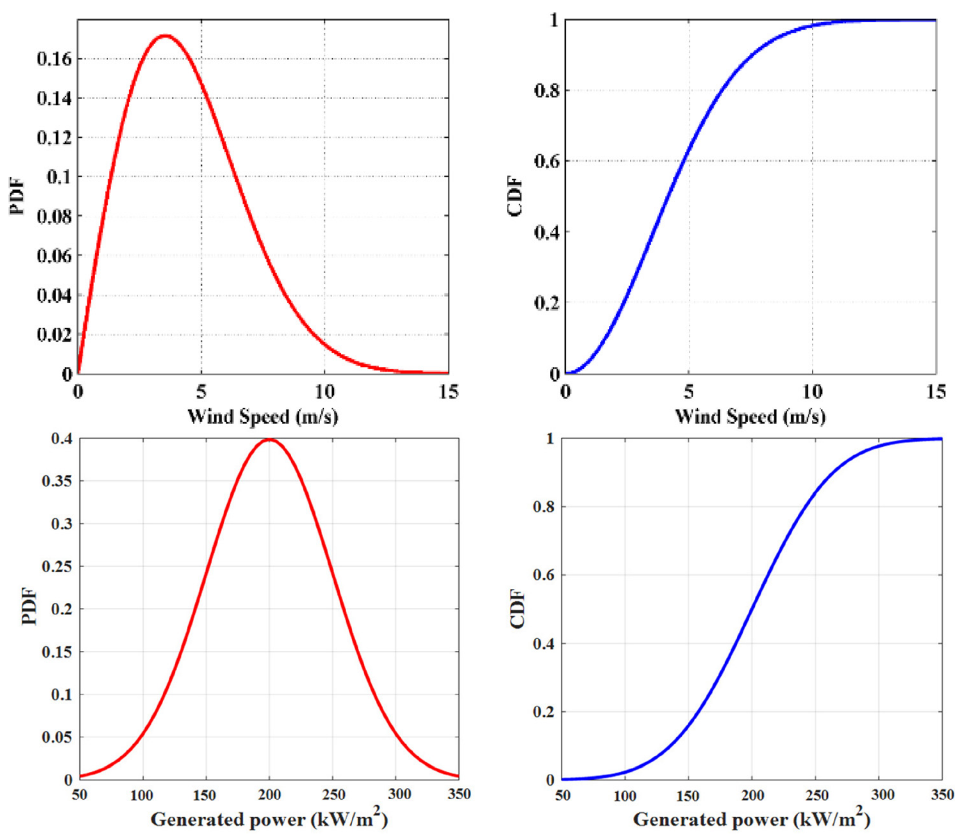

FIG. 2. PDF and CDF of WT and PV units.

(d) **Combined heat and power (CHP):** The CHP system is a combination of heat and power which generate the heat and power at the same time. Equation (27) defines the CHP system modelling

$$P_{c,t}^{\mathrm{CHP}} = \alpha + \beta P_{\mathrm{CHP}} + \gamma P_{\mathrm{CHP}}^2, \quad \forall c \in N_{\mathrm{CHP}}. \tag{27}$$

III. PROVIDING AN OVERVIEW ON THE MOPSO

A. Optimization algorithm

Regarding the proposed problem, it can be seen that it is a NP-complete problem with many complicating constraints. Therefore, it cannot be solved by exact methods. In so doing, in this paper, the MOPSO algorithm has been used to minimize all objective functions considered in the model simultaneously. The MOSPO has many advantages proportional to other multi-objective algorithms such as simplicity in implementation and speed in convergence which make it possible for large-scale optimization problems.[24]

Comparison of single-objective PSO algorithms with evolutionary algorithms suggests that using Pareto ranking can be a suitable solution for developing this algorithm to solve multi-objective optimization problems. Exterior repository is used to store the dominant answers that have been produced so far (similar to the evolutionary multi-objective optimization elitism concept). Exterior repository includes two sections of gridding and archiving, and the most important purpose is to maintain non-dominated vectors.

The repository controller determines whether or not a particular answer should be added to the repository, and the decision-making process is such that the non-dominated vectors that are obtained in each repetition of the algorithm are compared to the repository content that is initially null. If the exterior repository is null, then the current answers are acceptable. If the new answers are dominated from the repository, these answers will be deleted. If none of the exterior populations dominates the new answer, this answer will be stored in the repository. Eventually, if the external population reaches its maximum capacity, the gridding process will be implemented. The flowchart of the proposed algorithm to manage the congestion of the ADN is graphically shown in Fig. 4.

CM is a nonlinear program containing a large number of variables with various complicating constraints that can be solved by various optimization algorithms. In this paper, the recommended algorithm is MOPSO presented in Ref. 24. The concepts of MOSPO in searching the

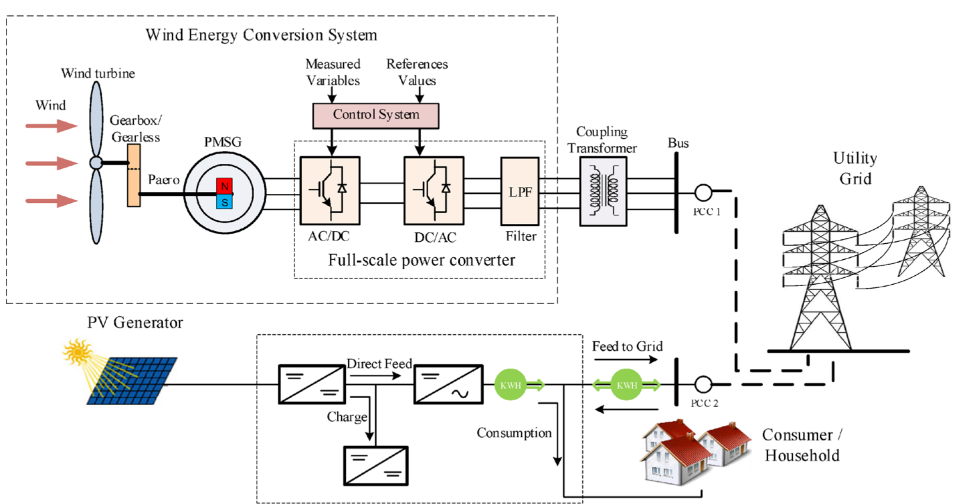

FIG. 3. Structure of hybrid solar-wind connection to the network.

best optimal solution are indicated in Ref. 24. The velocity update equation of MOPSO is as follows:

$$V_i(t+1) = wV_i(t) + (c_1 \times r_1)(P_i(t) - X_i(t)) + (c_2 \times r_2)(g(t) - X_i(t)). \tag{28}$$

Position update equations of MOSPO will be as follows:

$$X_i(t+1) = X_i(t) + V_i(t+1), \tag{29}$$

$$w = w_{\max} - ((w_{\max} - w_{\min})/\text{iter}_{\max}) \times \text{iter}, \tag{30}$$

$$V_{\max}(t) = V_{\max} - ((V_{\max} - V_{\min})/\text{iter}_{\max}) \times \text{iter}. \tag{31}$$

The steps of the proposed MOPSO algorithm to solve the proposed CM problem are briefly summarized as follows:

(1) Initialize the population.
(2) Initialize the velocity of each particle.
(3) Evaluate each particle of the population.

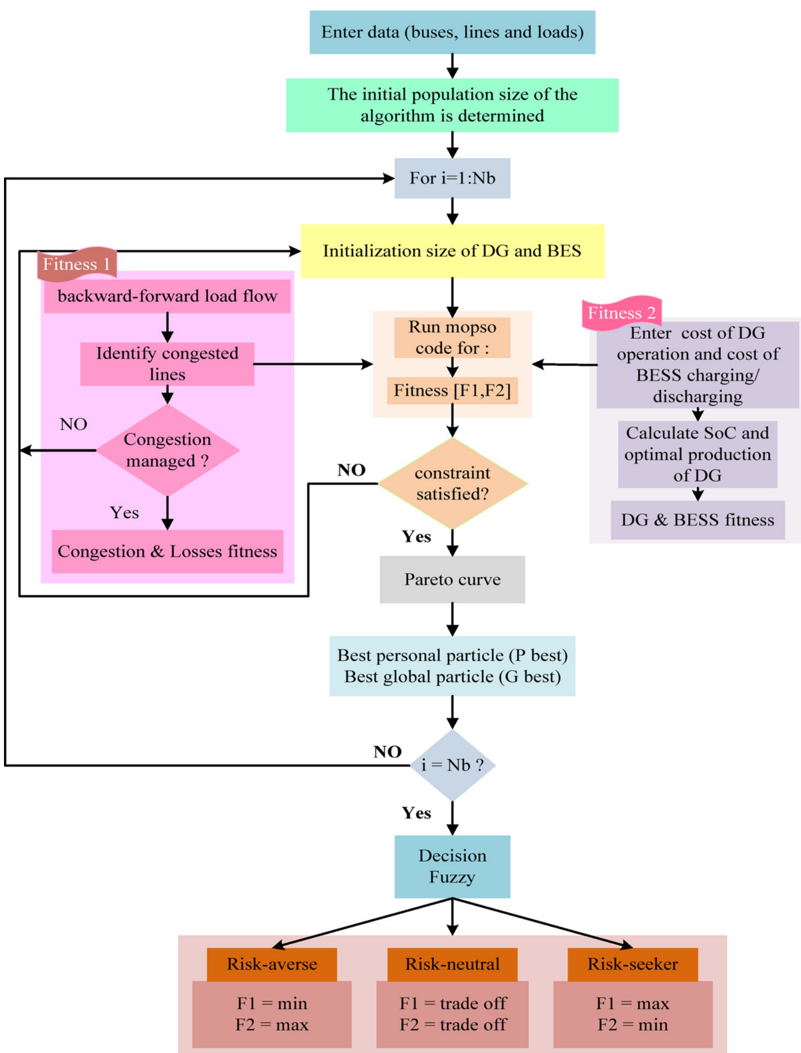

FIG. 4. Flowchart of the algorithms used for the proposed planning.

(4) Separate non-dominated population and store them in exterior repository.
(5) Tabulate the target space that is discovered.
(6) Each particle chooses one leader from members of repository and does its own move.
(7) Update the best personal of each particle.
(8) Non-dominated members of current population are added to the repository.
(9) Dominated members of repository are deleted.
(10) If the member of repository is more than specified capacity, delete extra members and renew tabulation.
(11) If the termination condition is not met, return to Step 5; otherwise, the process will end.

B. Fuzzy decision-making technique

The results of MOPSO will be a Pareto curve, where to extract one solution among these non-dominated solutions, an appropriate method should be taken. The proposed method for selecting the best solution is a fuzzy-based mechanism to elicit Pareto-optimal solution as the best agreement solution. Depending on the nature of the decision maker's arbitration, the objective function demonstrated by a membership function $H_i(x)$ is defined in Eq. (28) as presented in Ref. 32. It is worth noting that in this paper, the linear type of membership function (32) has been used for the decision-making process among the obtained Pareto curve[33]

$$H_i(x) = \begin{cases} 1, & \text{if } f_i(x) \geq Z_i, \\ 1 - \dfrac{Z_i - f_i(x)}{Z_i - z_i}, & \text{if } z_i < f_i(x) < Z_i, \\ 0, & \text{if } f_i(x) \leq z_i . \end{cases} \tag{32}$$

Normalized H_i for each non-dominated solution k is calculated using the following equation:

$$H^k = \frac{\sum_{i=1}^{N_{obj}} H_i^k}{\sum_{l=1}^{L} \sum_{i=1}^{N_{obj}} H_i^l}. \tag{33}$$

IV. SIMULATION RESULTS

A. Case study

The system under study is the modified IEEE 33-bus distribution network, whose technical information is presented in Refs. 34 and 35. In this network, we have assumed six sources of BES and six DG sources.[36] BES and DG sources have already been available and exploited in this network. The structure of the network utilized to implement the proposed model is illustrated in Fig. 5. BES and DG data are given in Tables I and II, which are obtained from Refs. 37–39. In addition, six different load profiles are utilized to implement the proposed model as demonstrated in Fig. 6 which are taken from Refs. 40–42.

B. Numerical results

The following figures indicate the optimal BES charge and discharge to prevent congestion in the ADN. In this section, the following three strategies are discussed:

(1) Risk neutral
(2) Risk seeker
(3) Risk averse.

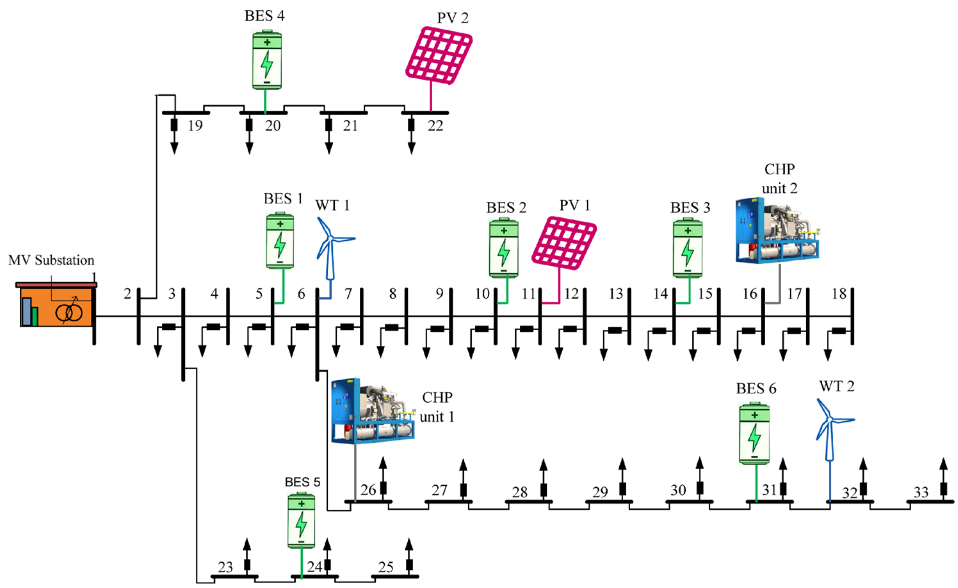

FIG. 5. IEEE 33-bus distribution network with BES and DG.

TABLE I. Technical data of utilized BES.

BES num.	SoC min	SoC max	Bus num.	Charge price ($/kW h)	Discharge price ($/kW h)	η_{ch}	η_{dis}
1	150	700	5	0.10	0.20	0.90	0.90
2	100	800	10	0.15	0.22	0.90	0.90
3	150	800	14	0.10	0.20	0.75	0.75
4	100	1000	20	0.30	0.45	0.85	0.85
5	100	800	24	0.09	0.15	0.85	0.85
6	100	700	31	0.09	0.15	0.90	0.90

TABLE II. Technical data of utilized DG units.

DG	Lower bound (kW h)	Upper bound (kW h)	Position (bus)	Cost factor ($/kW h)
1	200	600	6	0.02
2	200	500	11	0.05
3	150	450	16	0.01
4	100	400	22	0.05
5	200	700	26	0.01
6	200	600	32	0.02

The amount of charging and discharging of BES per hour is determined according to the consumer demand, the amount of generation of DG sources. For example, at 3 o'clock from SoC 1 and neutral risk, the BES is charged at 190 KW, which means that the output of the DG source in the network and upstream is higher than the consumption at that time, and the BES will charge as much as empty and vice versa.

It should be mentioned that the output of metaheuristic algorithms such as MOSPO highly depends on their parameters. The MOPSO searches to find the set of optimal solutions, the so-called Pareto front. The outer boundary of this collection of non-dominated points defines the limit beyond which the design cannot be further improved, bordering the region of feasible

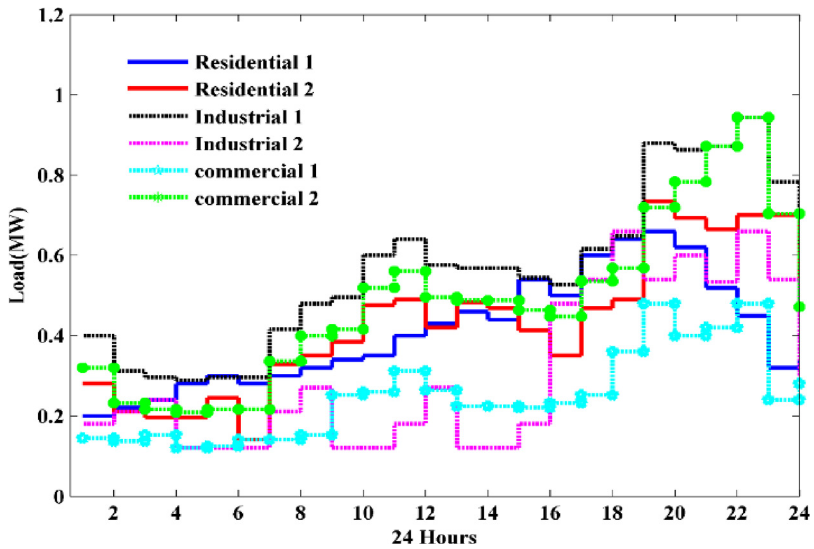

FIG. 6. Six different daily load profiles.

TABLE III. The effects of variations of MOPSO parameters on the problem.

				Risk-neutral		Risk-seeker		Risk-averse	
Case	C_1, C_2	W_{min}, W_{max}	V_{min}, V_{max}	F1	F2	F1	F2	F1	F2
1	**1, 1**	**1.2, 0.6**	**0.5, 0.2**	**172.20**	**1912.83**	**172.70**	**1890.26**	**172.06**	**1987.87**
2	1, 1	0.5, 0.4	0.4, 0.15	173.02	1921.58	173.10	1919.92	172.93	1940.44
3	1, 1.5	1, 0.5	0.4, 0.10	171.23	1816.05	171.37	1799.60	171.24	1817.66
4	1.5, 2	0.9, 0.4	0.35, 0.10	176.68	1624.54	272.08	1562.57	170.14	1761.82
5	1.5, 2	0.8, 0.4	0.25, 0.05	183.17	1704.81	625.49	1664.11	170.28	1849.56
6	1.5, 2	0.8, 0.5	0.25, 0.02	170.59	1698.45	252.82	1685.33	170.28	1798.72
7	2, 1.5	0.7, 0.3	0.2, 0.05	170.72	1637.89	228.63	1617.41	170.52	1687.45
8	2, 2	08, 0.5	0.25, 0.02	183.04	1665.95	601.27	1661.35	170.18	1806.96
9	2, 2	0.9, 0.4	0.2, 0.05	170.54	1515.40	182.73	1511.52	169.78	1593.77

solutions. Moving along the Pareto front, all the optimal trade-off solutions of the multi-objective problem can be found. In this paper, in order to investigate the impact of these parameters on the obtained solutions, a sensitivity analysis is fulfilled, and the results obtained from this analysis are depicted in Table III. By choosing each of these parameters, various results will be obtained for DSO. Therefore, DSO can choose the best solution based on its own strategy. Note that these results are shown based on the expected values of PDF considered for uncertain parameters. The PDFs of both objective functions for all strategies are shown in Fig. 7.

The results for optimal arbitrage of installed BES units for three risk strategies are shown in Fig. 8. The power scheduling of BES shows that electricity is stored (charged) when the answer of the equilibrium equation is negative and re-soles (discharged) when P_t^{rest} is positive. As can be seen from Fig. 8(a), from hours 1 until 12, the amount of P_t^{rest} is negative, but BES is charged from hours 1 to 5. From hours 6 until 12, the BES cannot be charged because the BES unit is fully charged. From hours 12 till 24, the load of the network increased and the amount of Eq. (13) is positive. In this period of day, BES in most of the time will be discharged.

From the aforementioned discussion, it is concluded that the amount of charge and discharge of the BES depends on the amount of DG production and requires the load of the

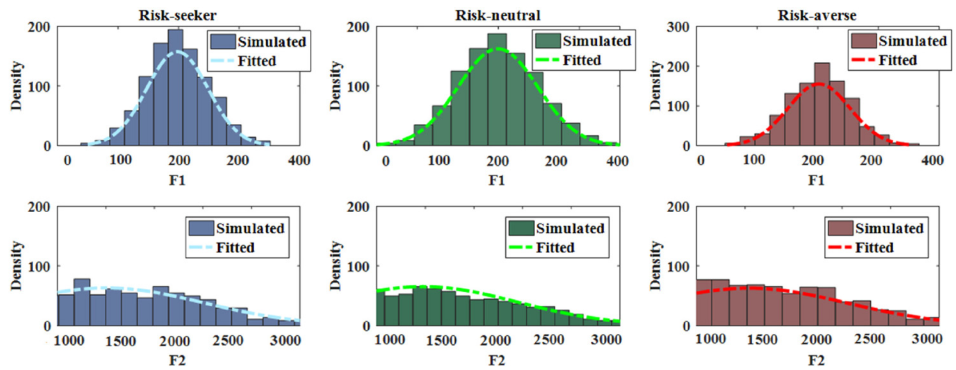

FIG. 7. PDF of objective functions for proposed risk-based strategies.

network at that time and the capacity of the BES. Note that the consumption level and the renewable generation level jointly determine the arbitrage potential of BES units; it is the electricity price variation rather than the absolute electricity price value that is crucial for the BES arbitrage.

The results of DG source production for all three strategies are shown in Fig. 9. According to these figures, the amount of power generated by DG sources per hour depends on their position in the feeder and the capacity of the DG sources (lower and upper bounds of installed DGs). Each column of figures shows the total power of six DG sources per hour. At 1:00 o'clock, the DG production of No. 6 had a production of 600 kW. Thus, it has the largest share in supplying the required network load at the same hour and battery charge. At 1 o'clock in Fig. 9(a), the operation cost and the capacity of DG1 and DG6 are the same due to the position of these sources in the network. Also, the main reason for the different production of DG sources is their optimal planning to avoid congestion per hour.

The optimal Pareto curve obtained from MOPSO is shown in Fig. 10 which is explained in Sec. III; all the dominated members are deleted, and the non-dominated members are retained. The best particle is the blue circle around it which is related to the neutral strategy. Black and red circles around the particle are related to risk averse and risk seeker, respectively. In this type of strategy, the DSO seeks to manage the congestion with the lowest possible cost, while the risk-averse DSO decreases the amount of power flow of lines by paying a high cost.

In other words, it uses the maximum capacity of the lines. In the risk neutral strategy, both cost and congestion are important for the DSO. Voltage profiles for all risk strategies defined for DSO are shown in Fig. 11 and compared with the initial voltage profile of the network. Also, the power losses of the network for all proposed risk-based strategies are graphically shown in Fig. 12. It should be stated that the distribution networks usually operate radially, and also, they have a high R/X ratio. Hence, traditional approaches for calculating the power flow computations such as Newton Raphson or Gauss Seidel are not applicable for these networks, especially in the presence of DGs. So, in this paper, the backward/forward sweeping algorithm has been successfully accomplished to calculate the power losses of the system in the presence of DG units and BESs. Due to the fact that the resistance of the network lines is always constant and does not change during the test, the CM reduces the power flow of lines, and thus, the power losses will decrease compared to the initial state.

The results of power flows in lines with and without applying the proposed method are presented in Fig. 13, so that the first column of the bar graph represents the nominal capacity of the 33 bus system lines. The second column of this graph represents the amount of initial active power flow (without DGs and BES). Finally, the rest of the three of columns after adding the DG resources and BES represent three strategies, namely, risk-neutral, risk seeker, and risk averse, respectively. By properly planning the DG production and scheduling of charging and

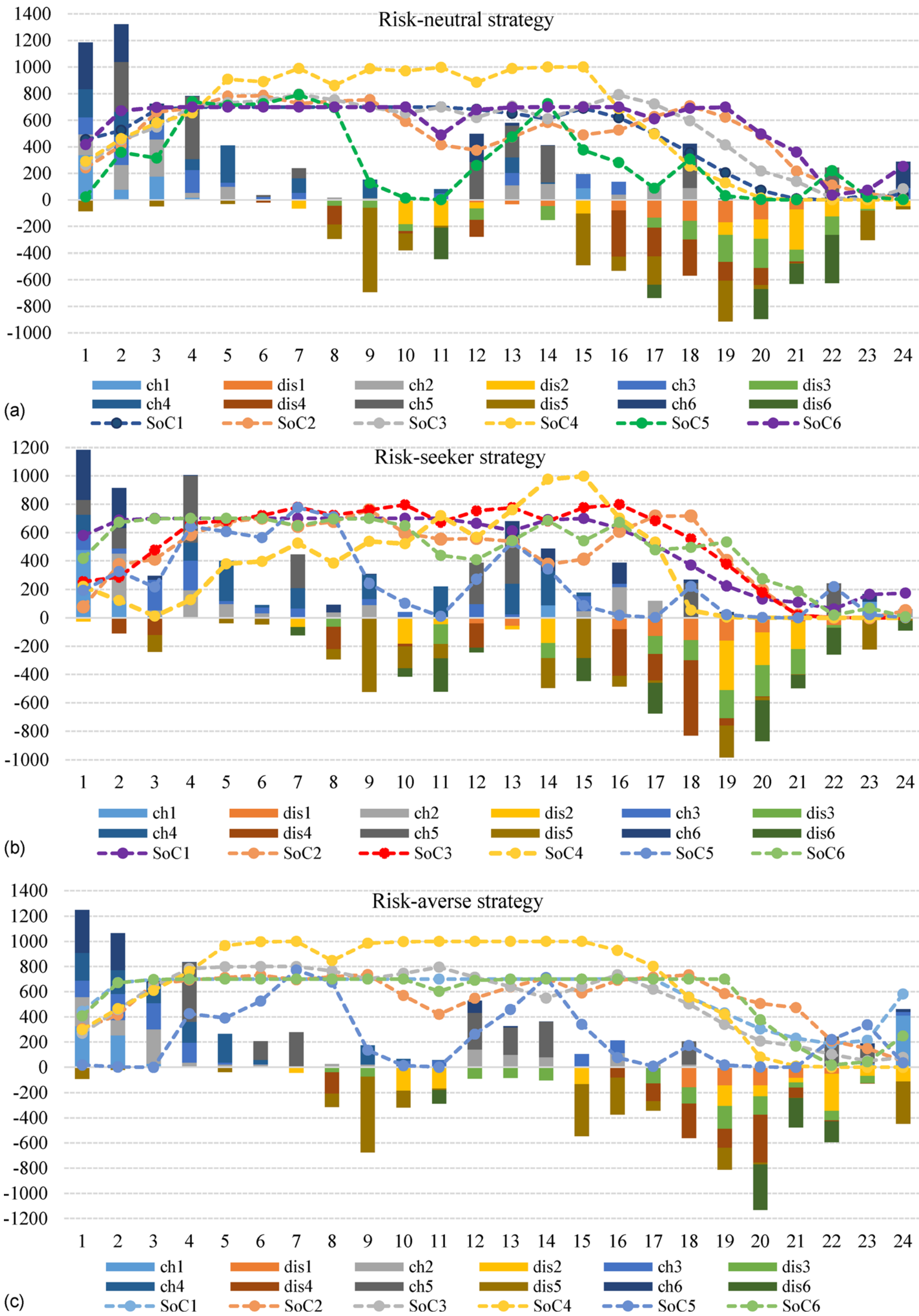

FIG. 8. Optimal day ahead arbitrage of DSS for all considered strategies.

discharging/discharging of the batteries at appropriate times, we were able to reduce the active power flow of the lines from the initial state and manage the congestion in the network lines.

Besides, in order to show the performance of the proposed algorithm compared to other algorithms for solving the proposed CM problem, the convergence curve of algorithms is shown in Fig. 14. The results obtained from numerical simulations indicate that with the use of BES units at the distribution networks, congestion probability, wind and solar curtailment, and re-dispatch costs of DG units are significantly decreased. Also, distribution line utilization owing to the operational rules of the BES units has been increased compared to the case where no

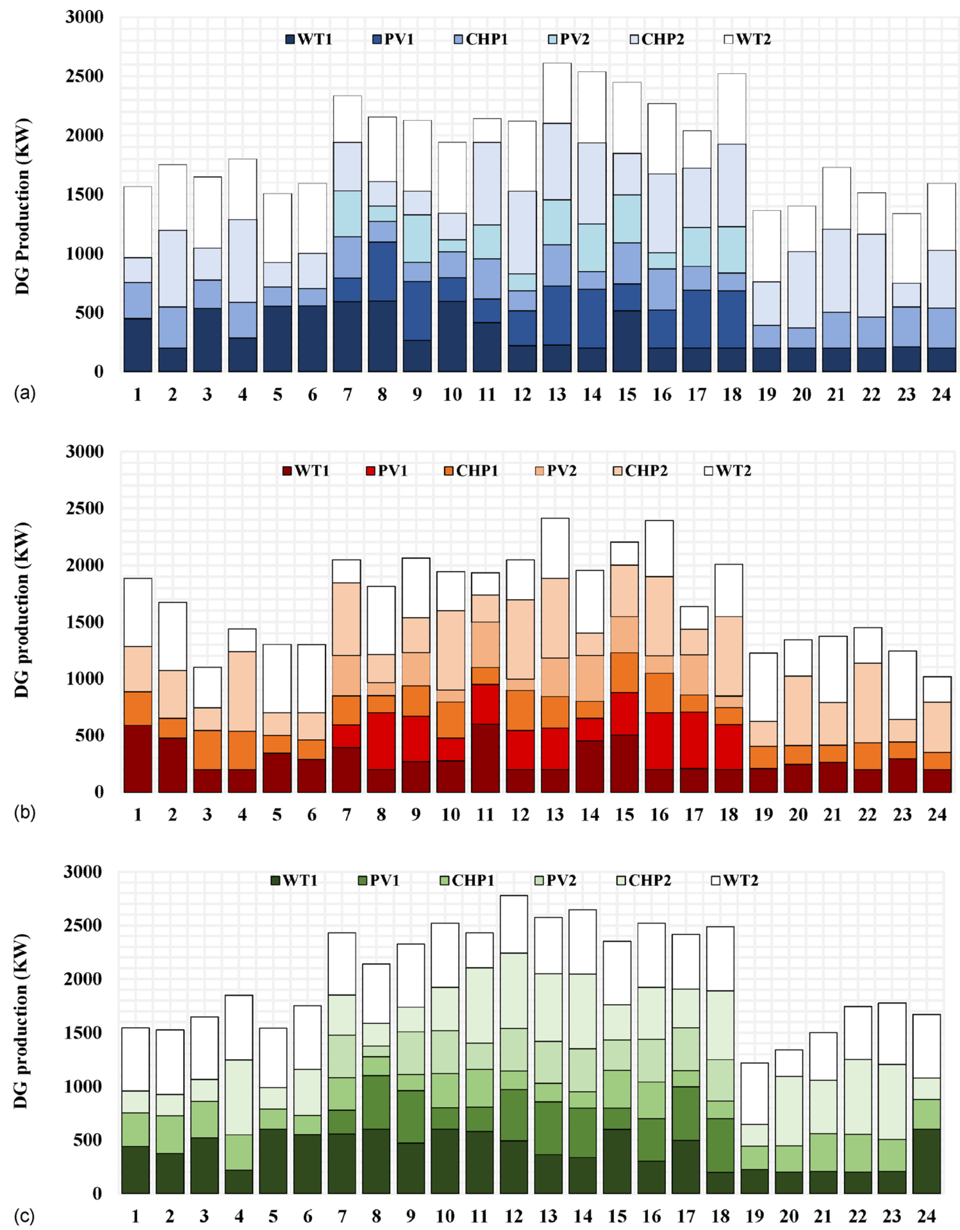

FIG. 9. Optimal DG productions for the risk neutral strategy.

BES units are in the network. Therefore, utilizing the BES units on the one hand improve the congestion of the system and on the other hand can reduce the operating costs of the system by smoothing the load profile of the system. It is worth noting that the smoothing the load profile has many profits for both DSO and consumers.

In general, the BES is charged and discharged at off peak and peak hours, respectively. To deal with the alternating PV and WT output powers, BES charging and discharging planning should be organized at least hourly, depending on load variations and intermittent outputs of PV and WT. If the interaction between batteries, PV/WT units, and loads is detected effectively, battery benefits will be achieved, such as reducing line losses, improving power quality, and also enhancing the reliability of the system.

To demonstrate the performance and privileges of the proposed model in comparison to previous works (such as re-scheduling of GENCO, demand response program, and FACTS devices), a comparative study is performed as shown in Table IV. As can be seen, the proposed

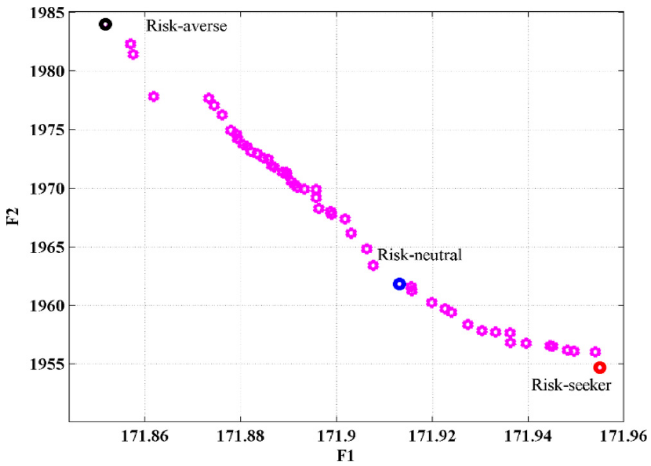

FIG. 10. Pareto repository obtained from MOPSO.

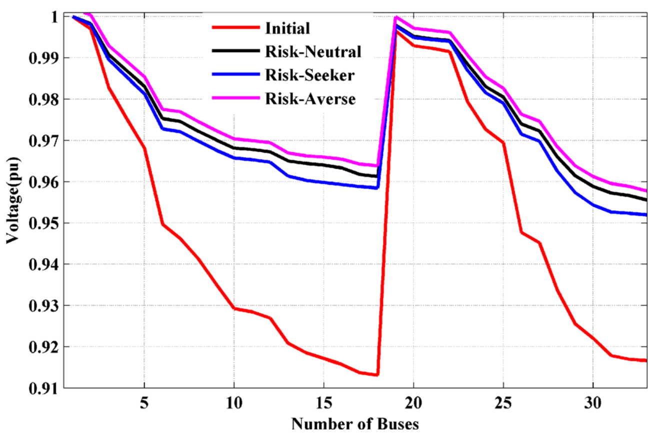

FIG. 11. Voltage profile of the 33 bus system for 3 strategies.

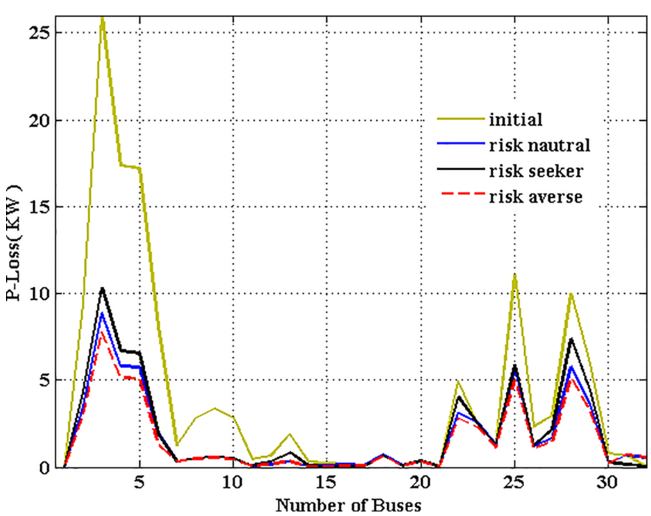

FIG. 12. Power losses of the network.

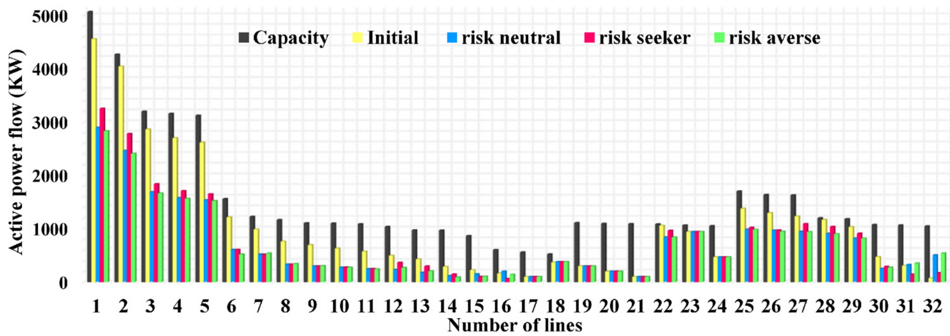

FIG. 13. Congestion analysis of lines.

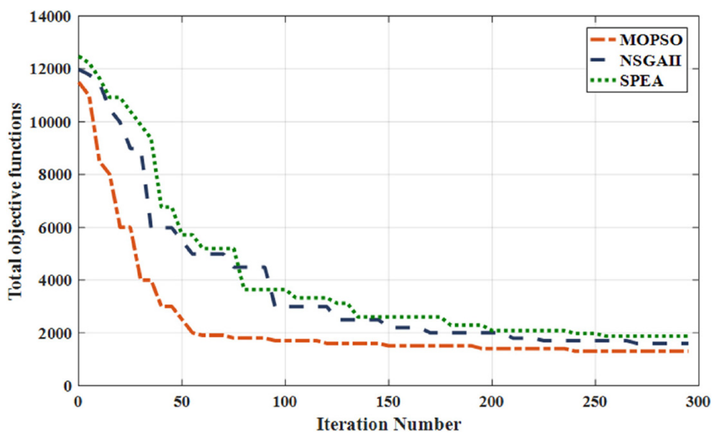

FIG. 14. Convergence curves of the proposed algorithm in comparison to other algorithms.

TABLE IV. Comparison study on different methods executed for the congestion management problem.

Reference	Proposed method	Case study	Congestion reduction (%)
This paper	Optimal arbitrage of dispersed BES including renewable and dispatchable DGs	IEEE 33-bus system	45.43 %
3	Demand response programs	IEEE 39-bus system	24.26 %
6	Demand response and FACT devices	IEEE 30-bus system	25.08 %
7	Re-scheduling of GENCOs	IEEE 30-bus system	27.55 %
10	Generation re-scheduling and load shedding	IEEE 118-bus system	29.41 %
11	Household demand response and distribution congestion prices	Danish 30-bus 60/10.5 kV system	16.94 %
13	Re-scheduling of conventional generators considering wind farms	IEEE 30-bus system	31.66 %

approach has had a greater impact on reducing congestion of the network compared to other existing methods. This is due to the fact that by distribution of the batteries and the DG units in the distribution network, the demand of each bus of the system is locally provided, and thus, it prevents the congestion of lines. In fact, at the off-peak periods, the BES systems are charged by surplus power of renewable resources and subsequently discharged into the network at the peak periods to provide a part of load locally. This energy arbitrage between BES systems and DG units significantly decreases the congestion of the network at peak hours.

V. CONCLUSION

In this paper, the optimal charging/discharging scheduling of BES units was addressed to manage the congestion of the ADN along with optimal operation of various DG resources. Also, the uncertainty pertaining to renewable resources was taken into account via applying a probabilistic model. The features of the proposed problem were non-linear, non-convex, and non-smooth, which is why we used the MOPSO algorithm to solve this NP-hard problem. The optimal arbitrage (charging/discharging) of BES units and optimal energy management of disparate DG units (wind, solar, and CHP) are obtained on the day ahead scheduling, considering the uncertainty of renewable generation via performing the probabilistic method. By applying the proposed scheme, DSO will be able to reduce the congestion and power losses in the lines of the system considerably, and also, it can be used to improve the technical specifications of the system such as security of the network in confronting the overloading, voltage profile, and stability margin of the network. Moreover, the results show that the BES units can reduce the curtailment energy of renewable resources and they can mitigate the severe uncertainty of the renewable generations. The results are compared with strategies, namely, three risk-neutral, risk-seeker and risk-averse. Regarding these risk-based strategies, it can be concluded that DSO can choose the best strategy based on its own characteristics in the decision-making process, which in turn obtains the best solution on the basis of DSO requirements.

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