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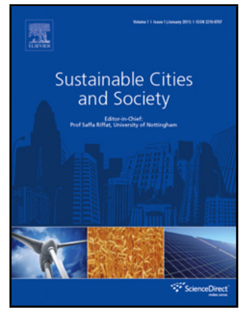

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Active Distribution Network Operation Management with Large Penetration of Hybrid Electric Vehicles and Sustainable Distributed Energy Generation

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Highlights:

- The optimal operation of active distribution networks in the presence of hybrid electric vehicles and sustainable distributed energy generation is addressed.
- An efficient analysis method to quantify the uncertainty related to the network operation is is provided.
- The correlation between sustainable energy generation sources is studied in the network operation.
- A probabilistic approach based on stoachastic optimization, equipped with a multi-criteria decision-making tool, is proposed to offer optimal decisions regarding the network operation under uncertainty.

Abstract- The unprecedented growth of technological advances, industrialization and sophisticated urbanization have contributed to a staggering proliferation of plug-in hybrid electric vehicles (PHEVs) and renewable energy sources (RESs) in transportation and electric power distribution systems. As a result, the nature of optimal distribution network operation is ever-changing due to the dramatic uncertainty in the increased energy supply and demand caused by large integration of these emerging technologies into the systems. This study proposes a synergistic approach for boosting power system operation performance in sustainable distribution networks considering renewable power generation and high integration of PHEVs, using multi-objective stochastic optimization and probabilistic analysis techniques. To this end, distribution network reconfiguration and evolutionary optimization schemes are deployed, and a probabilistic multi-criteria decision making (MCDM) system based on point estimate method is developed, considering stochastic correlation between distributed energy generation sources. The results obtained along with the performance appraisal observations, indicate the effectiveness of the proposed method in sustainable active distribution network operation management in their entirety.

Key words: *Active distribution network*; *Distributed energy generation; Hybrid electric vehicles*; *Multi-objective optimization*; *Sustainable energy*; *Uncertainty analysis*.

Nomenclature

P_l/Q_l	Active/ Reactive power of line *l*	N_{ec}/N_{ic}	Number of equality/inequality constraints
P_{ij}^t/Q_{ij}^t	Active/ Reactive power passing the line connecting buses *i* and *j* at time *t*	$N_{\square}^{m}$	Number of hypercubes containing archive members
P_i^t/Q_i^t	Active/reactive power injection to bus i at time *t*	$\boldsymbol{n}$	Number of input random variables (IRVs)
AER	All electric range, i.e. maximum distance that a fully charged PHEV can traverse	$numel(\square_i)$	Number of members in the *i*th hypercube
S_l^t	Apparent power of line *l* at time *t*	N_{ns}	Number of nondominated solutions
$C_{b,i}$	Battery capacity of the ith PHEV	$\boldsymbol{N_P}$	Number of populations
S_l^{max}	Capacity of line *l*	N_{OF}	Number of the objective functions

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$F_i^{-1}(.)$	CDF inverse of the random variable X_i	OF_i	Objective function *i*
$\Phi^{-1}(F_i(X_i))$	CDF inverse of the variables in the standard Normal space	$OF(X)$	Objective vector
$F_i(X_i)$	CDF of the random variable X_i	P_{wt}/P_r^{wt}	Output/ Rated power the wind turbine
$\Phi(Z_i)$	CDF of the random variable Z_i	$\boldsymbol{P}^*/\mathbf{PF}^*$	Pareto set/ Pareto front
$t; \mu_t, \sigma_t$	Charging start time of the PHEV and its mean and standard deviation	$\boldsymbol{f_t(t; \mu_t, \sigma_t)}$	PDF of the charging start time of PHEV
τ_c	charging time duration of PHEVs	$\boldsymbol{f_l(l; \mu_l, \sigma_l)}$	PDF of the load demand
$\boldsymbol{\lambda_{X_i,3}/\lambda_{X_i,4}}$	Coefficient of skewness/kurtosis of X_i	$\boldsymbol{f_m(m; \mu_m, \sigma_m)}$	PDF of the mileage variable
$\rho_{ij}/\rho_{ij}^{'}$	Components of correlation matrices C_X / C_Z	$\boldsymbol{f_{SoC}(SoC; \mu_m, \sigma_m)}$	PDF of the *SoC* variable
G_{ij}	Conductance of the line connecting buses *i* and *j*	$\boldsymbol{f(w: \alpha, \beta)}$	PDF of the wind speed
$C_X/C_Z/C_S$	Correlation matrix of random variables in the *X*, *Z* and *S* spaces	$\square_1^k/\Upsilon_2^k$	Penalty factor of equality / inequality constraints
$I_{l,max}$	Current capacity of line *l*	$\boldsymbol{X_{i,d}^t}$	Position of learner X_i at its dth dimension at time *t*

$I_{l,t}$	Current of the line *l* at time *t*	$\boldsymbol{X_i^t}$	Position of learner X_i at time *t*
w_{ci} w_{co} w_r	Cut-in/ Cut-out/ rated wind speed of wind turbines	$P_{i,t}^{PHEV}$	Power demand of PHEV *i* at time *t*
X /X_i	Decision vector/decision variable *i*	PDF	Probability distribution function
$\prec$ E T	Dominance/ expectation/ transpose operator	$\boldsymbol{randi}(\mathbf{0},\mathbf{1})$	Random integer number between [0,1]
$\eta_i^{c\square}$	Efficiency of the battery charger *i*	$\boldsymbol{r_i}$	Random number, uniformly distributed between [0,1]
Ω	Feasible region of decision variables	$P_r^{c\square}$	Rated power of the PHEV charger
$N_T(X)$	Forward Nataf transformation	R_l	Resistance of line *l*
Γ	Gamma function	R_{ij}/X_{ij}	Resistance/ Reactance of the line connecting buses *i* and *j*
$\boldsymbol{Y_h}$	h^{th} output variable	$round$	Round operator in mathematics
$\boldsymbol{F_h}(\boldsymbol{X})$	h^{th} response function of the system	$D(\square_i)$	Selection probability of hypercube *i* and random elimination of one of its members
S	Independent input variables in the standard Normal space	$L(\square_i)$	Selection probability of hypercube *i* and random selection of one of its members as leader

IRV	Input random variable	$\xi_{i,k}$	Standard location corresponding to $X_{i,k}$
$N_T^{-1}(S)$	Inverse Nataf transformation	$\boldsymbol{SoC}$	State of charge of PHEV
$\boldsymbol{iter}$ /$iter_{max}$	Iteration counter/ Maximum number of iterations	SoC_i^t	State of charge of PHEV *i* at time *t*
$g_j(X)$	j^{th} inequality constraint	k_l	Status index of line *l* (1=line is in service 0= line is out of service)
$\boldsymbol{Y_h^j}$	j^{th} raw moment of the h^{th} output variables	K_{ij}	Status index of the line connecting buses *i* and *j* (1=line in service; 0= line out of service)
$S_{i,k}$	k^{th} concertation point of IRV S_i in the standard Normal space	B_{ij}	Suseptance of the line connecting buses *i* and *j*
$X_{i,k}$	k^{th} concertation point of IRV X_i	$\boldsymbol{T_f}$	Teacher factor
$h_k(X)$	k^{th} equality constraint	$\boldsymbol{T_{i,j}}$	Teacher factor corresponding to individual *i* at learning material *j*
$l;\mu_l,\sigma_l$	Load demand and its mean and standard deviation	$\boldsymbol{t}$ /T	Time /time interval
μ_S	Mean of the random variables in the independent standard Normal (*S*) space	L /L^T	Upper and lower triangular matrices obtained from Cholesky decomposition
μ_X	Mean of the random variables in the original (*X*) space	$OF_{i,t}^{MCS} OF_{i,t}^{PM}$	Value of OF_i obtained from MCS/proposed method (PM)

M_j	Mean of the students' grade at learning material *j*	$OF_{i,t}^{EXP}$	Value of OF_i obtained from experiment
$\mu_{X_i}/\ \sigma_{X_i}$	Mean/standard deviation of IRV X_i	OF_i^m/OF_i^k	Value of the corresponding to mth/kth nondominated solution
μ_{Y_h}/σ_{Y_h}	Mean/standard deviation of the output variable	$Y_h(i,k)$	Value of the output random variable as a function of and other random variables
$\sigma_w/\ \mu_w$	Mean/standard deviation of wind speed	$\boldsymbol{var}$	Variance operator
$\mu_{OF_i}^t/\sigma_{OF_i}^t$	Mean/Standard deviation value of OF_i at time *t*	δ_i^t	Voltage angle of bus *i* at time *t*
μ_i^m	Membership function corresponding to OF_i^m	V_l	Voltage at the receiving end of line *l*
$m;\mu_m,\sigma_m$	Mileage and its mean and mean and standard deviation	$V_{i,t}$	Voltage of bus *i* at time *t*
V^{min}/V^{max}	Minimum/ Maximum voltage of the system (0.90 p.u./ 1.10 p.u)	$\omega_{i,k}$	Weight coefficient corresponding to $X_{i,k}$
$OF_i^{max}/\ OF_i^{min}$	Maximum/ Minimum value of OF_i	$w:\alpha,\beta$	Wind speed/ scale and shape factors of Weibull distribution

1. Introduction

1.1 Aim and Motivation

Recent advances in technology and sophisticated urbanization have promoted social welfare, and triggered a staggering utilization of PHEVs in the transportation system, leading to a significant energy demand increase in the electricity distribution sector. As a result, the loading level of electricity distribution lines and voltage drop of the system are more likely to rise considerably with the increased energy demand, causing voltage instability as well as dynamic and static power system security problems in the electricity distribution network. On the other hand, in recent years, the global attitude is increasingly changing towards renewable distributed generation to benefit from its extra economical, political and environmental advantages. However, distributed generation from renewable resources e.g. wind, is uncertain by its very nature, turning sustainable distribution network operation into a more challenging and intricate problem.

Given the above issues, the large-scale aggregation and integration of PHEVs and RESs into the distribution system can potentially propagate increased level of uncertainty across the entire power system (Samaie et al., 2020). Accordingly, improving grid voltage stability and load balancing indices along with power loss mitigation is vital to the safe, reliable and economic operation of the power system. On the other hand, research has shown adopting mean values for non-deterministic variables and neglecting possible stochastic dependencies between them would irreversibly contribute to decision making inexactitudes and egregious errors, in system studies, directly impinging optimal power network operation. Motivated by the above observations and necessities, this study develops an efficient probabilistic MCDM analysis (Mazzeo et al., 2020) for operation management of active distribution networks, considering correlation between sources of uncertainty.

1.2 Literature Review

1.2.1 Distribution network reconfiguration

In power system operation, distribution network reconfiguration (Tavakoli Ghazi Jahani et al., 2019) refers to the activity of finding optimal network topology with a feasible structure to attain some predefined goals. This task, which is generally practiced by utilities for different purposes such as power loss reduction, is carried out by altering the closed and open status of the network's switches, installed across electricity distribution lines. Mathematically, this problem is essentially considered a mixed integer, nonlinear, not-differentiable, constrained optimization problem, making evolutionary optimization approaches suitably qualified for solving it. Generally speaking, network reconfiguration techniques can be divided into three major groups, namely analytical, heuristic and meta-heuristic methods. Using analytical mathematical models, the first group actually proposes exact mathematical methodologies for solving network reconfiguration problem. Although these approaches enjoy a fast computation, yet they are incapable of handling large-scale problems with multiple objectives. Nevertheless, analytical network reconfiguration methods guarantee global optimal solution for simple network models (Carreno et al., 2008).

The second group is based on heuristic methodologies that can be found in the literature mainly for network loss reduction. Although heuristic methods are simple in terms of concept, and can present near global or even global solution, yet their application is mostly limited to medium-sized, single objective problems (Carreno et al., 2008). Finally, the third group typically employs meta-heuristic algorithms to find optimal solution(s) by stochastically exploring the entire search space of the problem. Considering the special characteristics of the reconfiguration problem, these methods are primarily applied to solve the problem with single or multiple objectives. Their ability to handle large scale distribution networks and generating a set of solutions in case of multi-objective optimization, altogether makes meta-heuristic approaches as effective approaches to handle the problem particularly for MCDM applications. However, they might suffer from premature convergence or even inefficient solutions as a result of inappropriate designs, which is discussed in more detail, subsequently.

1.2.2 Probabilistic uncertainty analysis techniques

A literature survey, in this context, shows these analysis methods can largely be classified into three main taxonomies, namely Numerical methods e.g. Monte Carlo simulation (MCS) (Cevallos-Torres & Botto-Tobar, 2019), analytical, e.g. cumulant approach (P. Zhang & Lee, 2004), and approximate methods, e.g. point estimate method (PEM) (Hong, 1998). The first group, is basically predicated on random generation of uncertain variables in sheer numbers and extensive simulations, thereby limiting their application due to expensive computational burden. Nevertheless, MCS is broadly used to provide a yardstick against other approaches. Although analytical methods might appear to be less time-consuming than MCS, yet the vast adoption of linearization techniques with complicated mathematical modelling, inevitably restricts their usage domain frequently to linear analysis problems. The second group of uncertainty analysis techniques is basically predicated on mathematical modelling and computation e.g. convolution and cumulant techniques, to derive the probability distribution function (PDF) of a linear combination of random variables. Although these methods might appear to be less time-consuming than MCS, yet the vast adoption of linearization techniques with complicated mathematical modelling and high storage capacity required, inevitably restricts their usage domain frequently to linear problems. Finally, though the third group may successfully be applied to assess the uncertainty vis-à-vis both linear and non-linear problems, however, these methods originally are incapable of tackling correlation between variables.

Considering this aspect and the above issues, this study proposes an efficient uncertainty analysis method for distribution network operation with large-scale integration of PHEVs and RESs, using Nataf transformation (Li et al., 2008) and PEM, which will be elaborated in more detail in the next sections. Table 1 presents a brief literature review on probabilistic uncertainty analysis techniques and their application in power system operation studies.

Table 1 Review of probabilistic uncertainty analysis techniques and their application in power system studies

Method	Main concept	Representative	Advantages	Disadvantages	Application
Numerical	- repeated generation and simulations of random numbers	- Monte Carlo simulation (MCS) (Cevallos-Torres & Botto-Tobar, 2019)	- salient accuracy - suitability for benchmarking applications due to high accuracy	- extremely high computational burden - not suitable for real or low time demanding applications	- energy purchase determination of distributed generation (DG) (Miri Larimi et al., 2016); DG placement (Xing & Sun, 2017)
Analytical	- linearization of response function - linear combination of random variables	- Convolution method (Anders, 1990) - Cumulant approach (Anders, 1990)	- suitable for uncertainty analysis of linear problems - fairly better speed performance compared to MCS	- lower accuracy - inability to produce high order moments - extensive computational burden - intricate mathematical modelling - high storage capacity	- probabilistic load flow based on convolution (Allan et al., 1981); probabilistic power flow based on cumulant (P. Zhang & Lee, 2004)
Approximate	- PDF approximation	- Point estimate method (PEM) (Hong, 1998)	- speed and accuracy - simplicity	- inability to handle correlation effect in its original framework	- load flow computation (Su, 2005); energy procurement (Khojasteh & Jadid, 2018)

1.2.3 Multi-objective optimization techniques

Given that virtually all real-world optimization problems by and large are multi-objective (MO) in their very nature, and the fact that the Utopian solution (a unique solution, considered as the best for any given objectives) seldom does exist, a set of solutions is frequently expected for these problems. Accordingly, it is essential to optimize these problems using MO optimization techniques. A literature survey in this context indicates that these methods can largely be divided into three primary categories, namely classical methods (e.g. weighted sum and ε -constraint methods), fuzzy optimization, and Pareto-based optimization methods. The weighted sum approach, simply transforms the MO problem to a single objective optimization (SO) problem with weighted linear combination of the objective functions, and subsequently solves it using scalar techniques. In ε -constraint method (Tavakoli Ghazi Jahani et al., 2019), one objective function is selected as the main objective function, while the others are treated as constraints, thereby adding to the complexity of handling a complicated constrained optimization problem with more constraints. The second group utilizes fuzzy principles to solve the problem without transmuting it to a SO one, however, the main concern is the generation of only a single solution, for the fuzzy search is basically designed to attain the specific solution with the highest fuzzy satisfaction degree. Contrary to the two previous methods, the third one neither converts the MO to a SO problem, nor limits the search to finding only a single alternative, instead they exploit Pareto dominance concept (Zitzler et al., 2008) in an attempt to produce a set of efficient solution alternatives. Table 2 presents a brief survey on different multi-objective optimization approaches with their application in power system studies. Besides the aforementioned issues, a deeper study of modern optimization principles indicate that some key measures should be taken into account when using MO optimizer. In this respect, an efficient optimizer must be able to generate a set of non-dominated solutions with maximum cardinality. Whilst these solutions ought to be scattered in a minimum distance to each other across the objective space, simultaneously they have to present a great diversity (Lee & El-Sharkawi, 2008), otherwise they would fail to produce effectual outputs. Considering the aforementioned issues, this study proposes a stochastic optimization to manage sustainable distribution network operation for multiple objectives including voltage stability, load balancing and power loss as implemented via reconfiguration of the network, which will be discussed in more detail in the following sections.

Table 2 Review of multi-objective optimization techniques and their application in power system studies

Method	Main concept	Representative	Advantages	Disadvantages	Application
Classical optimization	- Conversion of MO problem to SO problem	- Weighted sum approach (Zitzler et al., 2008) - ε constraint method (Zitzler et al., 2008)	- easy understanding - simple software implementation	- generation of only a single solution - severity for handling more constraints - restriction for MCDM application - convergence challenges	- reconfiguration of distribution networks (Tavakoli Ghazi Jahani et al., 2019); - Storage scheduling (Seyyedeh-Barhagh et al., 2019), appliance scheduling (Yahia & Pradhan, 2020),
Fuzzy optimization	- modelling the problem with fuzzy membership functions, fuzzy sets and rules	- Fuzzy centroid and and Fuzzy max-min approaches (Kahraman, 2008)	- operation in fuzzy domain rather than crisp universe - flexibility due to using linguistic varaibles	- Exclusive focus on finding the solution with the largest fuzzy satisfaction degree - generation of a single decision choice - sensitivity to the shape of Pareto front	- distribution network reconfiguration (Das, 2006) - Renewable energy generation (Suganthi et al., 2015)
Pareto-based	- Pareto dominance concept (Zitzler et al., 2008)	- NSGAII (Deb et al., 2002) - SPEA2 (Zitzler et al., 2001)	- ability to generate a set of efficient solutions - suitability for MCDM applications	- complexity in designing multi-objective optimizers and their implementation	- hybrid energy system design (Movahediyan & Askarzadeh, 2018) - distribution network reconfiguration (Andervazh et al., 2013)

NSGAII: Non-dominated sorting genetic algorithm II; SPEA2: Strength Pareto evolutionary algorithm 2

1.3 Contributions

The main contributions of this paper are as follows: (I) proposing heuristic optimization techniques for optimal operation of active distribution networks integrated with PHEVs and RESs. (II) Developing a stochastic method to quantify the uncertainty regarding transportation and electricity distribution systems operation, considering stochastic correlation between the variables. (III) Proposing an efficient probabilistic optimization algorithm to enhance the stability and operational performance of sustainable electricity distribution networks with large PHEVs integration in an uncertain environment. (IV) Developing a probabilistic MCDM operation management tool for distribution network operators to operate the network, optimally, considering high penetration of PHEVs and sustainable distribution energy generation sources.

1.4 Paper Organization

The rest of this paper proceeds as follows. Section 2 offers preliminaries to MO optimization and teaching learning based optimization, and section 3 presents the problem formulation. Section 4 present solution methodology. Section 5 presents simulation results and evaluates the performance of the proposed method by conducting a number of quantitative performance appraisal tests, and it finally concludes the paper by highlighting some main remarks.

2. Preliminaries

2.1. Multi-objective optimization

MO optimization involves solving a frequently constrained optimization problem with multiple objectives aimed at finding a specific solutions i.e. non-dominated solutions, characterized by (2) for minimization case problems. In this respect, vector $M = [M_1, \cdots, M_k]$ is said to dominate vector $N = [N_1, \cdots, N_k]$ i.e. $M \prec N$, if and only if M is partially less than N as mathematically described in (2).

$$OF(X) = [OF_1, \cdots, OF_i, \cdots, OF_{N_{OF}}]^T$$
$$\text{s.t.} \begin{cases} \square_k(X) = 0 & k = 1{:}\, N_{ec} \\ g_j(X) \leq 0 & j = 1{:}\, N_{ic} \end{cases}$$
$$X = [X_1, \cdots, X_i, \cdots, X_D]^T \qquad (1)$$

$$\forall\, i \in \{1, \cdots, k\}{:}\, M_i \leq N_i \ \wedge \ \exists\, i \in \{1, \cdots, k\}{:}\, N_i \leq M_i \qquad (2)$$

The set of such solutions is referred to as Pareto set (P^*), and their mapping onto the objective space is called Pareto front (PF*), respectively defined in (3) and (4).

$$P^*{:}= \{X \in \Omega \mid \neg\nexists Y \in \Omega \quad OF(Y) \prec OF(X)\} \qquad (3)$$
$$\text{PF}^*{:}= \{OF(X) \mid X \in P^*\} \qquad (4)$$

2.2. Teaching Learning Based Optimization (TLBO)

Inspired from social interactions, this algorithm mimics the smart teaching and learning pattern in human to solve optimization problems (Amirhosseini & Hosseini, 2018). In this regard, TLBO begins with a random population, simulating the best member as the teacher and the rest as learners. Then, the evolutionary algorithm executes two disparate modes i.e. teacher and learner, with the below functions to solve the problem.

- *Teacher Mode*

In this mode, the teacher endeavors to promote the knowledge of learners in learning material *j* to his level.

$X_{i,j}^{new} = round(X_{i,j}^{old} + r_i(T_{i,j} - T_f M_j))$ (5)

$T_f = 1 + randi(0,1)$ (6)

If $OF(X_i^{new}) \prec OF(X_i^{old})$ then X_i^{new} replaces X_i^{old} otherwise, the position of the learner remains unchanged.

- *Learner mode*

Each learner such as X_i, in this mode, attempts to improve his own knowledge by interacting with other learners such as X_k, as elaborated in (7).

$$\begin{cases} X_i^{new} = round(X_i^{old} + r(X_i - X_k)) & OF(X_i) \prec OF(X_k) \\ X_i^{new} = round(X_i^{old} + r(X_k - X_i)) & \text{otherwise} \end{cases} \quad k = 1{:}N_P \quad \text{and} \quad i \neq k \tag{7}$$

For more details, the interested reader is referred to (Rao et al., 2012).

3. Problem Formulation

3.1. Objective Functions

- Maximization of the voltage stability index (Arun & Aravindhababu, 2010)

$$OF_1(X) = V_{i,t}^4 - 4(P_{ij}^t X_{ij} - Q_{ij}^t R_{ij})^2 - 4(P_{ij}^t R_{ij} - Q_{ij}^t X_{ij})V_{i,t}^2$$

$i, j = 1,2, \dots, N_b \quad i \neq j \;\; ; \;\; t = 1, \dots, T$ (8)

- Minimization of the load balancing index (Saffar et al., 2011)

$OF_2(X) = var\left[\frac{S_1^t}{S_1^{max}} \quad \frac{S_2^t}{S_2^{max}} \quad \cdots \quad \frac{S_l^t}{S_l^{max}} []\right]$

(9)

- Minimization of the power losses

$OF_3(X) = \sum_{t=1}^{T} \sum_{j=1}^{N_l} \frac{k_l R_l (P_l^2 + Q_l^2)}{|V_l^2|}$ (10)

X is the decision variables' vector, determining configuration of the network.

3.2. Constraints

- Power balance equations

$$P_i^t - V_{i,t} \sum_{j=1}^{N_b} V_{j,t} K_{ij}\big(G_{ij}\, cos(\delta_i^t - \delta_j^t) + B_{ij}\, sin(\delta_i^t - \delta_j^t)\big) = 0$$

$Q_i^t - V_{i,t} \sum_{j=1}^{N_b} V_{j,t} K_{ij}\big(G_{ij}\, cos(\delta_i^t - \delta_j^t) - B_{ij}\, sin(\delta_i^t - \delta_j^t)\big) = 0$

(11)

- Voltage limit

$V^{min_{i,t}max} \quad i = 1,2, \dots, N_b$ (12)

- Current limit

$k_l |I_{l,t}| \leq I_{l,max} \quad l = 1,2, \dots, N_l$ (13)

- Charging limit of PHEVs

$P_{i,t}^{PHEV} \leq P_r^{c□}$ (14)

- State of charge (SoC) of HEVs

$0.1 \leq SoC_i^t \leq 1$ (15)

- Connectivity and radial operation constraints

$k_l \times N_l = N_b - 1$

(16)

To satisfy this constraint, graph theory techniques proposed in (Andervazh et al., 2013) are deployed.

4. Methodology

4.1. Boosting the Performance of Evolutionary MO

Owing to fact that most evolutionary MO algorithms generally use an external archive to restore non-dominated solutions obtained during optimization, and that storage capacity is size-limited, it is crucial to keep it within the limits. In contrast to other approaches in the literature that simply the truncate archive to reduce the size, a heuristic strategy is proposed in this section to manage the archive's size effectively throughout optimization. In addition, since leader (a specific individual responsible to guide the search) plays a crucial role in the success of optimization, a heuristic method is also proposed here to boost the performance of MO by choosing efficient leaders.

4.1.1. Archive size management procedure

- Split the explored objective space into a cellular grid using adaptive grid algorithm (Knowles & Corne, 2003).
- Identify those cells containing archive members.
- Attribute a probability to these cells, using (17).

$$D(\square_i) = \frac{exp(numel(\square_i))}{\sum_{i=1}^{N_{\square}^{m}} exp(numel(\square_i))} \tag{17}$$

- Select the cell with the maximum probability.
- Reduce the archive size by randomly discarding a member from the selected cell.
- Continue the above process till reaching the desired size.

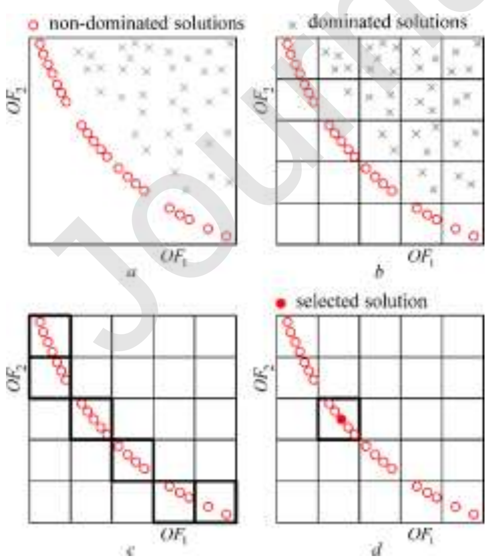
4.1.2. Leader selection procedure

- Split the explored objective space into a cellular grid using adaptive grid algorithm.
- Specify those cells consisting archive members.
- Assign a probability to these cells, using (18).

$$L(\square_i) = \frac{exp(-numel(\square_i))}{\sum_{i=1}^{N_{\square}^{m}} exp(-numel(\square_i))} \tag{18}$$

- Select the cell with the maximum probability.
- Determine a leader by randomly choosing a member from the selected cell.

Figs. 1 and 2 provide a better insight into the procedures by illustrating the whole process.



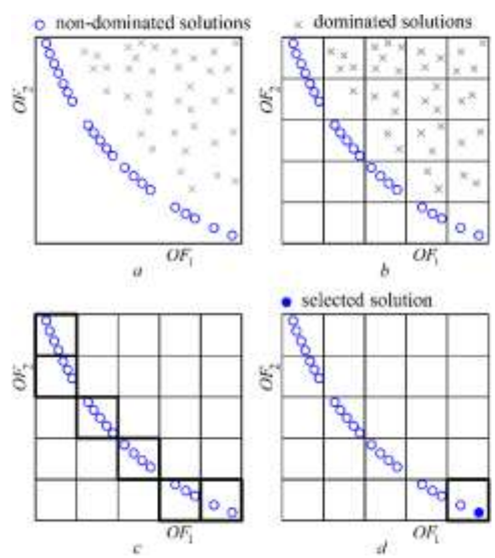


Fig. 1. Archive size management procedure.
(a) Objective space representation, (b) Objective space division, (c) Identification of the cells containing archive members, (d) member deletion from the cell with the maximum probability.

Fig. 2. Leader selection procedure.
(a) Objective space representation, (b) Objective space division, (c) Identification of the cells containing archive members, (d) leader selection from the cell with the maximum probability

4.2. Modelling of PHEVs

4.2.1. Daily mileage of the vehicles

Research has shown daily distance traversed by PHEVs follows a log-normal distribution (Qian et al., 2011).

$$f_m(m;\mu_m,\sigma_m)=\frac{1}{m\sqrt{2\pi\sigma_m^2}}exp\left(-\frac{(ln\,m-\mu_m)^2}{2\sigma_m^2}\right);m>0 \tag{19}$$

- SoC of PHEVs' Battery

This variable indicates the state of charge of the vehicle that is a function of the daily mileage and the maximum distance that a fully charged vehicle can traverse.

$$SoC=1-\frac{m}{AER}\ ;\ 0<m\le AER \tag{20}$$

Submitting (19) to (20), (21) statistically describesSoC.

$$f_{SoC}(SoC;\mu_m,\sigma_m)=\frac{1}{(1-SoC)\sqrt{2\pi}\sigma_m}exp\left(-\frac{(ln(1-SoC)+ln\,AER-\mu_m)^2}{2\sigma_m^2}\right) \tag{21}$$

4.2.2. Charging start time of the vehicles

Figures and statistics have shown that this random variable follows a normal probability distribution function (PDF) (Qian et al., 2011).

$$f_t(t;\mu_t,\sigma_t)=\frac{1}{\sigma_t\sqrt{2\pi}}exp\left(-\frac{(t-\mu_t)^2}{2\sigma_t^2}\right) \tag{22}$$

4.2.3. Charging duration of PHEVs

This variable (τ_c), which is a function of the PHEV battery and its charger characteristics, actually describes the required time to charge a PHEV battery to its full charge state.

$$\tau_c=\frac{C_{b,i}\times(1-SoC_i^t)}{\eta_i^{c\square}P_r^{c\square}} \tag{23}$$

4.3. Load demand modelling

Recent practical distribution system studies suggest that uncertainty in load demand typically follows normal PDF (Milani & Haghifam, 2013).

$$f_l(l;\mu_l,\sigma_l)=\frac{1}{\sigma_l\sqrt{2\pi}}exp\left(-\frac{(l-\mu_l)^2}{2\sigma_l^2}\right) \tag{24}$$

4.4. Wind power production

Renewable energy studies indicate that wind speed variations follow Weibull distribution denoted in (25).

$$f(w:\alpha,\beta)=\frac{b}{\alpha}\left(\frac{w}{\alpha}\right)^{\beta-1}exp\left(-(\frac{w}{\alpha})^{\beta}\right)$$

$$\beta=\frac{(\sigma_w}{\mu_w)^{-1.086}}\quad\text{and}\quad\alpha=\frac{\mu_w}{\Gamma(1+(1/\beta))} \tag{25}$$

The power produced from wind turbines can be computed using (26).

$$P_{wt} = \begin{cases} P_r^{wt} & w_r \le w \le w_{co} \\ ((w^3 - w_{ci}^3)/(w_r^3 - w_{ci}^3))P_r^{wt} & w_r \le w \le w_{co} \\ 0 & w \le w_{ci} \vee w \ge w_{co} \end{cases}$$
(26)

4.5. Uncertainty quantification

4.5.1. $2n + 1$*PEM* (Hong, 1998)

Assume a system with *n* input random variables (IRVs) and *h* response functions, i.e. $Y_{\square} = F_{\square}(X) = F_{\square}(X_1, \cdots, X_i, \cdots, X_n)$, PEM employs the first few moments of IRVs to quantify the uncertainty in output variables as follows:

- For each IRV, compute three specific points, defined by (27), as concentration points.

$$X_{i,k} = \mu_{X_i} + \xi_{i,k}\sigma_{X_i} \quad i = 1,2,\ldots,n \ ; \quad k = 1{:}\,3 \tag{27}$$

$$\xi_{i,k} = \begin{cases} \frac{\lambda_{X_i,3}}{2} + (-1)^{3-k}\sqrt{\lambda_{X_i,4} - \frac{3}{4}\lambda_{X_i,3}^2} & k = 1,2 \\ 0 & k = 3 \end{cases} \tag{28}$$

$\lambda_{X_i,3}$ and $\lambda_{X_i,4}$ are the skewness and kurtosis coefficients of X_i defined in (29) and (30), respectively.

$$\lambda_{X_i,3} = \frac{E\left[(X_i - \mu_{X_i})^3\right]}{\sigma_{X_i}^3} \tag{29}$$

$$\lambda_{X_i,4} = \frac{E\left[(X_i - \mu_{X_i})^4\right]}{\sigma_{X_i}^4} \tag{30}$$

- Designate a weight to the above concentration points.

$$\omega_{i,k} = \begin{cases} \frac{(-1)^{3-k}}{\xi_{i,k}(\xi_{i,1} - \xi_{i,2})} & k = 1,2 \\ \frac{1}{n} - \frac{1}{\lambda_{X_i,4} - \lambda_{X_i,3}^2} & k = 3 \end{cases} \tag{31}$$

- Calculate the *j*th raw moment of the output variables.

$$E[Y_{\square}^j] = \omega_0\left(F_{\square}(\mu_{X_1}, \ldots, \mu_{X_i}, \ldots, \mu_{X_n})\right)^j + \sum_{i=1}^{n}\sum_{k=1}^{2} \omega_{i,k}\,(Y_{\square}(i,k))^j$$

$$\omega_0 = 1 - \sum_{i=1}^{n} \frac{1}{\lambda_{X_i,4} - \lambda_{X_i,3}^2}$$

$$Y_{\square}(i,k) = F_{\square}(\mu_{X_1}, \mu_{X_2}, \ldots, X_{i,k}, \ldots, \mu_{X_n}) \tag{32}$$

4.5.2. Nataf transformation (Li et al., 2008)

Let $X = [X_1, \cdots, X_i, \cdots, X_n]$ defines a vector consisting *n* correlated input random parameters, each following any marginal probability distribution in the original variable space referred to as *X*-space in this study. Using (35), these variables can be reproduced from the dependent normal vector *Z* in the dependent normal space referred to as *Z*-space herein.

$$F_i(X_i) = \Phi(Z_i) \leftrightarrow X_i = F_i^{-1}(\Phi(Z_i)) \tag{33}$$

Let C_X and C_Z express the correlation between the IRVs in the *X* and *Z* spaces, respectively. The component of these matrices can be estimated using relation (34). For the family of Weibull distribution, (40) describes function $H(\cdot)$(Liu & Der Kiureghian, 1986).

$$C_X = \begin{bmatrix} 1 & \cdots & \rho_{1j} & \cdots & \rho_{1n} \\ \vdots & \ddots & \rho_{ij} & \ddots & \vdots \\ \rho_{n1} & \cdots & \rho_{nj} & \cdots & 1 \end{bmatrix} \quad \text{and} \quad C_Z = \begin{bmatrix} 1 & \cdots & \rho'_{1j} & \cdots & \rho'_{1n} \\ \vdots & \ddots & \rho'_{ij} & \ddots & \vdots \\ \rho'_{n1} & \cdots & \rho'_{nj} & \cdots & 1 \end{bmatrix} \tag{34}$$

$$\rho'_{ij} = H(\rho_{ij})\rho_{ij} \quad (35)$$

$$H = 1.063 - 0.04\rho_{ij} - 0.2(\delta_i + \delta_j) - 0.001\rho_{ij}^2 + 0.337(\delta_i^2 + \delta_j^2) + 0.007\rho_{ij}(\delta_i + \delta_j) - 0.007\delta_i\delta_j) \quad (36)$$

Where $\delta_i = \frac{\sigma_{X_i}}{\mu_{X_i}}$ and $\delta_j = \frac{\sigma_{X_j}}{\mu_{X_j}}$

Using Cholesky decomposition (37), the symmetric matrix C_Z can be decomposed into two upper and lower triangular matrices.

$$C_Z = LL^T \quad (37)$$

Then the correlated vector X is reproducible in the independent standard normal space as follows:

$$Z = LS \leftrightarrow S = L^{-1}Z \quad (38)$$

$$S = N_T(X) = T_2 \circ T_1(X) \quad (39)$$

$$T_2 : X \to Z = \begin{bmatrix} \Phi^{-1}(F_1(X_1)), \cdots, \Phi^{-1}(F_i(X_i)) \\ , \cdots, \Phi^{-1}(F_n(X_n)) \end{bmatrix}$$

$$T_1 : Z \to S = L^{-1}Z \quad (40)$$

Using inverse NT, the independent standard normal vector $S = [S_1, \ldots, S_i, \ldots, S_n]$ can be mapped to the X space.

$$X = N_T^{-1}(S)$$

$$N_T^{-1} : X_i = F_i^{-1}(\Phi(LS)) \quad (41)$$

4.5.3. The proposed uncertainty quantification method

In this part, an efficient method based on $2n + 1$ PEM (Hong, 1998) is developed to handle correlation effect between random variables in the distribution system, as per the following steps.

- Using (36), determine C_Z for a given C_X .
- Using (37), determine the lower triangular matrix L.
- Map the first four statistical moments of the variables onto the independent standard normal space.

$$\mu_S = L^{-1}\mu_X \quad (42)$$

$$C_S = L^{-1}C_Z(L^{-1})^T = I \quad (43)$$

$$\lambda_{S_i,q} = \sum_{r=1}^{n}(L_{ir}^{-1})^q \lambda_{X_r,3}\sigma_{X_r}^q \; ; \; q = 3,4 \; ; \; i = 1{:}n \quad (44)$$

- Determine the concentration points and their weights in the standard normal space (SNS), using (27)-(31).
- Considering mean values, for each concentration point, construct the vector denoted in (45).

$$[\mu_{S_1}, \mu_{S_2}, \ldots, S_{i,k}, \ldots, \mu_{S_n}] \qquad i = 1{:}n \;\; ; \;\; k = 1{:}3 \quad (45)$$

- Transform the above organised vectors from SNS into the original space, using inverse *NT*.
- Estimate $Y_h(i,k)$ corresponding to each X_i calculated from the above step.
- Estimate the statistical properties of $Y_{\square}$ using (46).

$$\mu_{Y_{\square}} = E[Y_{\square}]$$

$$\sigma_{Y_{\square}} = \sqrt{E[Y_{\square}^2] - (E[Y_{\square}])^2} \quad (46)$$

The PDF and cumulative distribution function (CDF) of the output variables can be determined using Cornish-Fisher expansion, based on the above statistical properties, the (Usaola, 2009).

4.5.4. Multi-Criteria Decision-Making (MCDM)

As indicated in the introduction, solution of a typical MO problem is generally a set of solutions rather than a single choice. This part introduces a fuzzy MCDM approach to facilitate decision making in system operation by discerning the best trade-off solution (BTS) obtained from MO optimization.

For this purpose, each OF_i is modeled by a fuzzy membership function (FMF), and the value of each FMF regarding each non-dominated solution m i.e. μ_i^m is evaluated. Then, the normalized FMF value (μ^m) associated with each solution is evaluated, considering preferences of the decision-maker (DM) as modeled by different weight coefficients. BTS is the particular solution that demonstrates the maximum value for μ^m (Zhu, 2009).

$$\mu^m = \frac{\sum_{i=1}^{N_{OF}} W_i \cdot \mu_i^m}{\sum_{m=1}^{N_{ns}} \sum_{i=1}^{N_{of}} W_i \cdot \mu_i^m} \quad \sum_{i=1}^{N_{OF}} W_i = 1; \quad 0 \le W_i \le 1 \tag{47}$$

$$\mu_i^m = \begin{cases} 1 & OF_i^m \le OF_i^{\min} \\ \dfrac{OF_i^{\max} - OF_i^m}{OF_i^{\max} - OF_i^{\min}} & OF_i^{\min} < OF_i^m < OF_i^{\max} \\ 0 & OF_i^{\max} \le OF_i^m \end{cases} \tag{48}$$

4.6. The proposed active distribution network management method

1) Input active distribution network and transportation system data together with MO algorithm.
2) Convert the MOP into an unconstrained one using (49).

$$OF(X) = \begin{bmatrix} OF_1 + \Upsilon_1^k \sum_{j=1}^{N_{ec}} |\square_j(X)| + \Upsilon_2^k \sum_{k=1}^{N_{ic}} (max[0, \quad g_k(X)])^2 \\ OF_2 + \Upsilon_1^k \sum_{j=1}^{N_{ec}} |\square_j(X)| + \Upsilon_2^k \sum_{k=1}^{N_{ic}} (max[0, \quad g_k(X)])^2 \\ OF_3 + \Upsilon_1^k \sum_{j=1}^{N_{ec}} |\square_j(X)| + \Upsilon_2^k \sum_{k=1}^{N_{ic}} (max[0, \quad g_k(X)])^2 \end{bmatrix} \tag{49}$$

$\square_1 = \square_2 = 100$ and $k = \frac{iter}{iter_{max}}$

3) Generate the initial population, that is:
$X = [X_1, \cdots, X_i, \cdots X_{N_P}]^T$ P
$X_i = [X_i^1, \cdots, X_i^t, \cdots X_i^T]^T$
$X_i = [X_{i,1}^t, \cdots, X_{i,d}^t, \cdots X_{i,D}^t] \quad d = 1{:}D$
4) Evaluate the population, using (46) and (49).
5) Store non-dominated solutions in an external archive.
6) Partition the searched objective space into a hyper-cube plane, and discern cubes containing archive members as described in the previous section.
7) Implement the leader selection procedure, and TLBO.
8) Evaluate the population, using (46) and (49).
9) Update the archive with non-dominated solutions, and run archive size management procedure.
10) While $iter \neq iter_{max}$ go to step six, else discern BTS using the introduced fuzzy MCDM.

5. Results and discussion

This section presents the results obtained from implementing the proposed method on a large-scale network containing 119 buses, 118 branches with 15 sectionalizing switches and 6000 PHEVs with the information presented in (D. Zhang et al., 2007) and Table A1. The vehicles are distributed in proportion to the demand at load buses. Each PHEV uses a 3kW chargers installed at home plug-in stations, with an efficiency of 92%. In terms of mileage, a typical PHEV-30 generally traverses an average distance equal to $\mu_m = 25$ with $\sigma_m = 7$ miles, while for a typical PHEV-15, these values drop down to 13 and 7 miles, respectively. Among different PHEVs' charging scenarios, in this study it is assumed that 80% of PHEVs (equivalent to 4800 vehicles) adopt smart charging strategy (Veldman & Verzijlbergh, 2015) for charging the vehicles, thereby imposing a lower energy cost to consumers due to charging in off-peak hours with providing the added benefit of representing a better network load factor for utilities. Whereas the remaining 20% of vehicles (equivalent to 1200 PHEVs) charge their batteries in an uncoordinated charging fashion. Table A2 represents the information regarding the mentioned charging strategies.

The system also incorporates six wind parks installed at buses 51, 55, 72, 75, 110 and 112. Each wind park contains ten 5kW wind turbines (model Aeolos-H5) with $v_{ci} = 3, v_{ci} = 10$ and $v_{co} = 25$ (m/s) equipped with local power factor correction facilities. The wind parks are correlated with each other with a correlation coefficient of 0.65, whereas turbines situated within the same wind park depict a correlation coefficient of 0.95 with respect to each other. To be pragmatic, the wind speed pattern together with the load trend of Tehran city on 6 February 2019 as shown in Fig. 3 have been used in simulations. Load demand at each bus follows a normal PDF with σ_l of 5% from their corresponding mean values reported in (D. Zhang et al., 2007). Table A3 represents values regarding the MO optimization algorithm parameters.

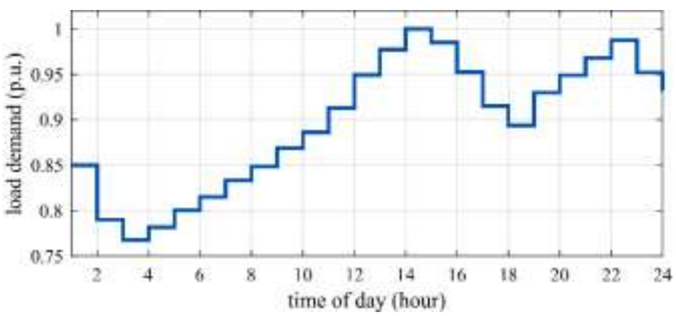


Fig. 3. Expected load demand normalized by 22.70 MW

5.1. Simulation Results

The statistical properties of the network's hourly solutions integrated with PHEVs and RESs are presented in Table 3. As an emblematic figure of the total hours, the CDFs of the variables with the Pareto front associated with the night peak hour are depicted in Figs. 4 and 5, respectively.

Table 3 Statistical properties of the hourly best trade-off solutions. (W1= W2=W3=0.33)

t	$\mu_{OF_1}^t$	$\sigma_{OF_1}^t$	$\mu_{OF_2}^t$	$\sigma_{OF_2}^t$	$\mu_{OF_3}^t$	$\sigma_{OF_3}^t$	*Decision variables*	*Expected demand (MW)*
1	0.5672	0.0213	0.0516	0.00145	778.23	94.16	24-27-35-43-52-59-72-75-96-98-110-123-125-130-131	22.631
2	0.5968	0.0198	0.0456	0.00128	687.93	83.31	24-27-35-43-52-59-72-75-96-98-110-123-125-130-131	21.408
3	0.6040	0.0195	0.0440	0.00124	665.56	80.78	24-27-35-43-52-59-72-75-96-98-110-123-125-130-131	21.162
4	0.5925	0.0200	0.0458	0.00129	704.91	85.74	24-27-35-43-52-72-75-96-98-110-123-124-125-130-131	21.493
5	0.5875	0.0202	0.0505	0.00142	692.95	83.92	24-26-35-43-51-59-72-75-96-110-122-125-129-130-131	21.600
6	0.5907	0.0201	0.0468	0.00131	718.60	86.62	24-27-35-43-52-72-75-96-98-110-123-124-125-130-131	21.462
7	0.5940	0.0200	0.0471	0.00132	710.22	85.03	24-27-35-43-52-59-72-75-96-98-110-123-125-130-131	21.406
8	0.6020	0.0197	0.0470	0.00131	706.47	83.95	24-27-35-43-52-59-72-75-96-98-110-123-125-130-131	21.202
9	0.6062	0.0196	0.0477	0.00133	713.69	84.22	24-27-35-43-52-59-72-75-96-98-110-123-125-130-131	21.149
10	0.6133	0.0193	0.0479	0.00134	709.79	82.91	24-27-35-43-52-59-72-75-96-98-110-123-125-130-131	20.969
11	0.6254	0.0189	0.0489	0.00136	716.41	82.62	24-27-35-43-52-59-72-75-96-98-110-123-125-130-131	20.957
12	0.6365	0.0185	0.0508	0.00140	733.18	83.19	24-27-35-43-52-59-72-75-96-98-110-123-125-130-131	21.053
13	0.6103	0.0197	0.0548	0.00152	803.03	92.18	24-27-35-43-52-59-72-75-96-98-110-123-125-130-131	21.982
14	0.5979	0.0203	0.0573	0.00159	841.33	96.68	24-27-35-43-52-59-72-75-96-98-110-123-125-130-131	22.465
15	0.6074	0.0199	0.0554	0.00153	809.35	92.70	24-27-35-43-52-59-72-75-96-98-110-123-125-130-131	22.031
16	0.6343	0.0186	0.0513	0.00142	741.08	84.22	24-27-35-43-52-59-72-75-96-98-110-123-125-130-131	21.119
17	0.6466	0.0179	0.0475	0.00131	686.25	78.02	24-27-35-43-52-59-72-75-96-98-110-123-125-130-131	20.413
18	0.6449	0.0180	0.0462	0.00128	672.8	77.09	24-27-35-43-52-59-72-75-96-98-110-123-125-130-131	20.285
19	0.6071	0.0197	0.0518	0.00144	768.15	89.45	24-27-35-43-52-59-72-75-96-98-110-123-125-130-131	21.680
20	0.5905	0.0205	0.0553	0.00154	824.77	96.82	24-27-35-43-52-59-72-75-96-98-110-123-125-130-131	22.519
21	0.5784	0.0211	0.0587	0.00164	874.23	103.14	24-27-35-43-52-59-72-75-96-98-110-123-125-130-131	23.263
22	0.5607	0.0219	0.0622	0.00174	928.33	110.10	24-27-35-43-52-59-72-75-96-98-110-123-125-130-131	24.044
23	0.5511	0.0223	0.0601	0.00168	905.89	108.48	24-27-35-43-52-59-72-75-96-98-110-123-125-130-131	23.951
24	0.5357	0.0229	0.0602	0.00169	912.83	110.31	24-27-35-43-52-59-72-75-96-98-110-123-125-130-131	24.233

It can be recognized from Fig. 5 that the proposed method offers a spectrum of different alternatives to the active distribution network operator (ADNO), making decision-making more efficient and straightforward under uncertain operating environment. In this respect, it is observed that each scenario can contribute to improving the operational performance of the distribution network in terms of power losses, voltage stability and load balancing indices. The ADNO can choose a proper operating scenario, considering his preferences and network demand. Fig. 6 represents load demand after the integration of RESs and vehicles to the power network. As it can be observed from Figs. 3 and 6, the network experiences a fundamental change in its energy demand after grid integration of PHEVs and renewables. In this regard, it can also be perceived that day and night peak hours have been shifted to other times. In addition, the results presented in Fig. 6 implicitly indicates a better network load factor compared to the previous network state before PHEVs and RESs integration.

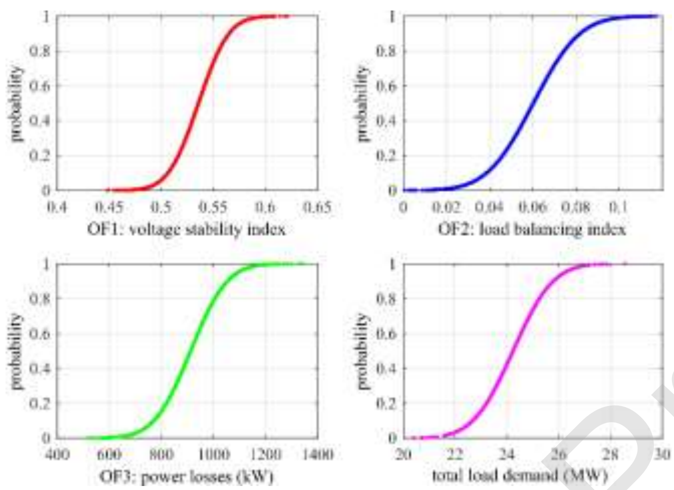


Fig. 4. CDF of the objective functions at night peak hour

In order to make a direct comparison with other methods, the deterministic results of the proposed method are contrasted with other approaches in the literature. For this purpose, each objective is separately optimized, neglecting the presence of wind sources and PHEVs. The comparative results presented in Table 4 indicate the effectiveness of the proposed method in terms of SO optimization. In addition, the results, respectively, show 57%, 46% and 34% improvement in voltage stability, load balancing and losses vis-à-vis the initial network configuration.

Table 4 performance assessment results in terms of single-objective optimization

method	Decision variables (open switches)	OF_i
case-1		OF_1
proposed method	24-26-35-40-43-51-59-72-75-96-98-110-122-130-131	0.5719
PSO	24-33-51-59-71-109-119-120-122-125-126-127-129-130-131	0.4330
GA	24-27-40-43-59-72-75-96-98-110-122-123-130-131-133	0.4282
case-2		OF_2
proposed method	24-27-35-43-52-59-72-75-96-98-110-123-125-130-131	0.0750
PSO	24-27-40-43-59-72-75-96-98-110-122-123-130-131-133	0.0994
GA	24-27-40-45-52-59-72-75-96-98-123-130-131-132-133	0.1164
case -3		OF_3 (kW)
proposed method	24-26-35-40-43-51-59-72-75-96-98-110-122-130-131	850.97
method in (D. Zhang et al., 2007)	24-27-35-40-43-52-59-72-75-96-98-110-123-130-131	866.67
method in (Abdelaziz et al., 2013)	24-27-35-40-43-52-59-72-75-96-98-110-123-130-131	866.67
method in (Mishima et al., 2005)	23-27-33-40-43-49-52-62-72-74-77-83-110- 126-131	884.16
PSO	24-27-35-40-43-52-59-72-75-96-98-110-123-130-131	866.67

GA	24-27-35-40-43-52-59-72-75-96-98-110-123-130-131	866.67
Initial configuration	119-120-121-122-123-124-125-126-127-128-129-130-131-132-133	OF_1=0.3642 OF_2=0.1385 OF_3=1298.01 (kW)

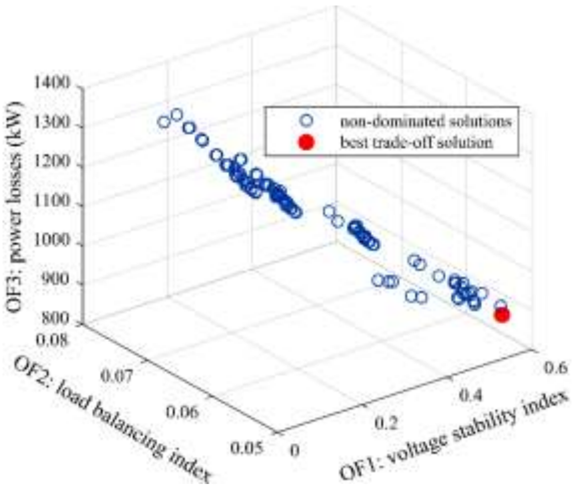


Fig. 5. Pareto front obtained at night peak

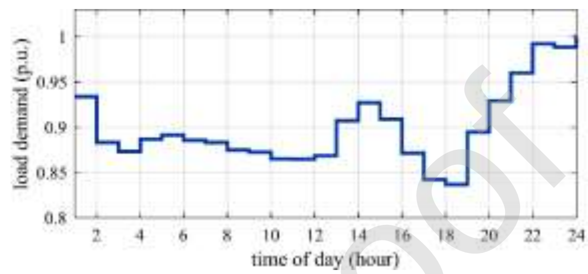


Fig. 6. Load demand after reconfiguration of the network with PHEVs and RESs

5.2. Performance Appraisal (PA)

5.2.1. Uncertainty analysis

To conduct this PA, first, using Nataf transformation, 15000 random correlated samples are constructed for MCS, then the presented problem is solved for each sample deterministically. To assess the performance from the viewpoint of accuracy, the results obtained, as presented in Table 5, are benchmarked against MCS results, by measuring the relative error denoted in (50).

$$REI = \left(\frac{|OF_{i,t}^{MCS} - OF_{i,t}^{PM}|}{OF_{i,t}^{MCS}}\right) \times 100\ \% \qquad i = 1{:}N_{OF} \tag{50}$$

Table 5 Performance assessment result in terms of uncertainty quantification at day and night peak hours

Hour		Statistical characteristics	$\mu_{OF_1}^t$	$\sigma_{OF_1}^t$	$\mu_{OF_2}^t$	$\sigma_{OF_2}^t$	$\mu_{OF_3}^t$ *(kW)*	$\sigma_{OF_3}^t$ *(kW)*	*t (sec)*
14:00	method	proposed method	**0.5979**	**0.0203**	**0.0573**	**0.00159**	**841.33**	**96.68**	**~60**
		MCS	0.5970	0.0201	0.0568	0.00158	838.74	96.28	~660
	index	*REI (%)*	0.1508	0.9950	0.8803	0.6329	0.3088	0.4155	
24:00	method	proposed method	**0.5357**	**0.0229**	**0.0602**	**0.00169**	**912.83**	**110.31**	**~60**
		MCS	0.5349	0.0226	0.0598	0.00168	910.18	109.82	~660
	index	*REI (%)*	0.1496	1.3274	0.6689	0.5962	0.2912	0.4462	

DR: deterministic results

Herein, $\mu_{OF_i}^t$ and $\sigma_{OF_i}^t$ are the mean and standard deviation of the objective function *i* at time *t*, respectively.

Observing the results of this experiment indicate the effectiveness of the proposed method in uncertainty quantification regarding the presented problem by showcasing a considerable statistical accuracy achieved with a lower computational burden.

5.2.2. Multi-objective optimization

To conduct the PA, some pivotal performance metrics together with state-of-the-art MO evolutionary algorithms i.e. NSGA-II (Deb et al., 2002) SPEA2 (Zitzler et al., 2001) have been deployed.

- Spacing metric (Sm)

$$Sm = \sqrt{(N_{ns}-1)^{-1}\sum_{i=1}^{N_{ns}}\left(\overline{d}-d_m\right)^2}$$

$$\overline{d} = \sum_{m=1}^{N_{ns}}\frac{d_m}{N_{ns}}$$

$$d_m = min_k\sum_{i=1}^{N_{OF}}\left|OF_i^m - OF_i^k\right|$$

$$k = 1,\dots,N_{ns} \text{ and } m \neq k \quad (51)$$

A smaller Sm value translates to a better distribution of solutions in the objective space (Lee & El-Sharkawi, 2008).

- Diversity metric (Dm)

$$Dm = \sqrt{\sum_{i=1}^{N_{OF}}\left(OF_i^{\max} - OF_i^{\min}\right)^2} \quad (52)$$

A higher Dm value corresponds to a better PA in terms of diversity (Lee & El-Sharkawi, 2008).

- Final number of Pareto solutions (FNS)

By merging all solutions obtained from MO algorithms and discarding possible dominated members, this measure conducts PA from the viewpoint of cardinality measure. The larger the value of FNS the better is the performance.

Table 6 presents the results obtained from conducting performance evaluation for the night peak hour. As it can be observed, the proposed method shows a better performance in comparison with NSGA-II (Deb et al., 2002) and SPEA2 (Zitzler et al., 2001) in terms of all the performance indicators. A similar trend was observed for the other hours of the day.

Table 6 Performance assessment results in trems of MO optimization

Method	Metric	*FNS*	*DI*	*SP*	*t (sec)*
Proposed method	Best	**104**	**488.38**	**9.19**	**~60**
	Avg.	103.25	487.45	9.22	65.05
	Std. dev.	0.85	0.89	0.02	5.30
NSGA-II	Best	8	168.30	11.99	~345
	Avg.	6.65	164.72	12.15	368.45
	Std. dev.	1.13	2.58	0.12	27.02
SPEA2	Best	12	459.50	27.98	~500
	Avg.	10.45	457.47	28.37	530.30
	Std. dev.	1.70	1.65	0.30	38.50

5.3. Impact assessment of uncertainty

In order to highlight the impact of uncertainty on optimal active distribution network operation management, in this part, two more experiments have been carried out. In the first experiment, uncertainty across the entire distribution network is totally neglected. In this respect, the deterministic results corresponding to the selected hours are evaluated and compared with the probabilistic results obtained from the proposed method. Similarly, the day and night peak hours have been chosen as representative samples of the total daily hours. The results of this experiment as presented in Table 7, pinpoint the profound impact of uncertainty on the output variables by showcasing considerable relative error index values vis-à-vis voltage stability, load balancing and power loss across the active distribution network.

$$REI = \left(\frac{|OF_{i,t}^{PM} - OF_{i,t}^{EXP}|}{OF_{i,t}^{PM}}\right) \times 100\ \% \qquad i = 1{:}\,N_{OF} \tag{53}$$

Table 7 Results of the first experiment

Hour		ouput characteristics	$\mu_{OF_1}^t$	$\mu_{OF_2}^t$	$\mu_{OF_3}^t$ (kW)
14:00	method	Proposed method (PM)	0.5979	0.0573	841.33
		Deterministic experiment (EXP)	0.4384	0.0783	1023.20
		REI (%)	26.68	36.65	21.62
24:00	method	Proposed (PM)	0.5357	0.0602	912.83
		Deterministic experiment (EXP)	0.4189	0.0812	1086.70
		REI (%)	21.80	34.88	19.05

The second experiment conducts a quantitative impact analysis of correlated uncertainty in the distribution network operation by totally neglecting the stochastic dependencies between network variables. To do so, the probabilistic results of the network management without considering the correlation effect between the random variables are evaluated and compared with the results squired from implementing the proposed method. The statistical results of this experiment as depicted in Table 8 highlight the correlation effect between network variables by demonstrating considerable changes in the statistical properties of the the network output variables. In particular, this observation is more palpable by observing the the relative error values concerning voltage stability, load balancing and power loss associated with this experiment.

Table 8 Results of the second experiment

Hour		Output characteristics	$\mu_{OF_1}^t$	$\sigma_{OF_1}^t$	$\mu_{OF_2}^t$	$\sigma_{OF_2}^t$	$\mu_{OF_3}^t$ (kW)	$\sigma_{OF_3}^t$ (kW)
14:00	method	Proposed method (PM)	0.5979	0.0203	0.0573	0.00159	841.33	96.68
		Probabilistic experiment (EXP)	0.4987	0.0235	0.0675	0.00193	719.55	110.48
		REI (%)	16.59	15.76	17.80	21.38	14.47	14.27
24:00	method	Proposed method (PM)	0.5357	0.0229	0.0602	0.00169	912.83	110.31
		Probabilistic experiment (EXP)	0.4589	0.0271	0.0705	0.00210	808.61	129.25
		REI (%)	14.34	18.34	17.10	24.26	11.42	17.17

5.4. Effect of correlation

This part addresses the effect of correlation between stochastic variables by investigating this phenomenon in active electric power distribution networks and its impact on distribution network operation. To do so, the night peak hour is selected as sample of the daily hours, and the correlation coefficient is changed from 0.35 to 0.95 with step 0.1. Fig. 7 depicts correlated wind speed samples for two selected wind parks in the distribution network.

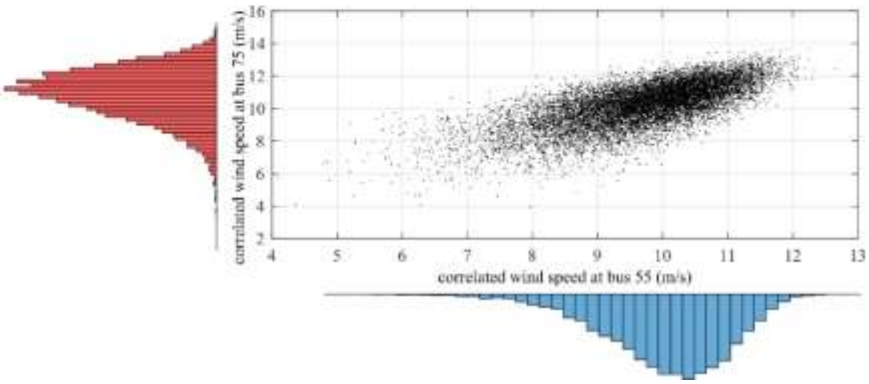


Fig. 7. Correlated wind speed samples at wind parks

The results depicted in Table 9, indicate the standard deviation of power losses, voltage stability and load balancing indices change conspicuously with changes in correlation coefficient between the random variables. It can be inferred from these experiments that the existence of correlation between stochastic variables may introduce significant technical risks to the operation of active distribution networks integrated PHEVs and renewable energy resources.

Table 9 Effect of correlation

$\mu_{OF_1}^t$	$\sigma_{OF_1}^t$	$\mu_{OF_2}^t$	$\sigma_{OF_2}^t$	$\mu_{OF_3}^t$ (kW)	$\sigma_{OF_3}^t$ (kW)	CC
0.5357	0.0229	0.0602	0.00169	912.83	110.31	0.95
0.5784	0.0211	0.0587	0.00164	874.23	103.14	0.85
0.5905	0.0205	0.0553	0.00154	824.77	96.82	0.75
0.5672	0.0213	0.0516	0.00145	778.23	94.16	0.65
0.5925	0.0200	0.0458	0.00129	704.91	85.74	0.55
0.5968	0.0198	0.0456	0.00128	687.93	83.31	0.45
0.6040	0.0195	0.0440	0.00124	665.56	80.78	0.35

CC: correlation coefficient

5.5. Conclusion

This paper proposed a synergistic method to bring succor to active distribution network operators to effectively operate sustainable distribution networks in the presence of high integration of HEVs and RESs. The results presented indicated the effectiveness of the proposed method in uncertainty quantification and optimization of the active electric power distribution system operation by improving the operational performance of the power system through minimizing losses, and improving voltage stability and load balancing indices in the network.

Appendix

Voltage stability index changes from 1 (at no load) to 0 (at voltage collapse point), and for node *j* connected to node *i* through line *l* depicted in Fig. A.I, can be calculated using (1).

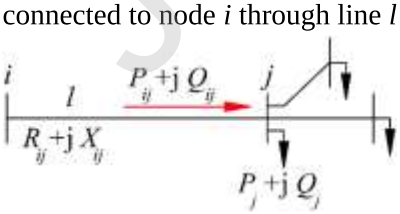


Fig. A.1. Sample electricity distribution line.

Table A1 Characteristics of the PHEVs

Vehicle type	PHEV-15 (kWh)	PHEV-30 (kWh)	Consumption (kWh/mile)
Compact sedan	3.9	7.8	0.26
Mid-size sedan	4.5	9	0.3
Mid-size SUV	5.7	11.4	0.38
Full-size SUV	6.9	13.8	0.46

Table A2 Charging strategies and their statistical characteristics of the PHEVs

Charging strategy	No. of vehicles participating in the strategy	Charging start time (hour)
Smart charging	4800	$\mu_t = 2, \sigma_t = 4$
Uncoordinated charging	1200	$\mu_t = 10, \sigma_t = 4$ $\mu_t = 14, \sigma_t = 4$ $\mu_t = 18, \sigma_t = 4$

Table A3 Parameter values of the MO optimization algorithm

Parameters	$N_P = 20$	*archive size*=100
	$iter_{max}$	Number of space divisions by the adaptive arid algorithm=20

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