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A Robust Renewable Energy Source-oriented Strategy for Smart Charging of Plug-in Electric Vehicles Considering Diverse Uncertainty Resources

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A B S T R A C T

Nowadays, the notion of plug-in electric vehicle (PEV) as a valuable tool of energy management has been extensively employed in smart distribution grids. The main advantage of clean energy as well as elastic behaviour of operation in both electrical load/generation modes can sufficiently justify the utilization of such emerging technology. Moreover, the specific capability of renewable energy sources (RESs) in terms of contribution in PEV smart charging/discharging scheme would cause to remarkable techno-economic benefits in smart grids. However, the load demand, RES generation and also the electrical energy price encounter with uncertainty in practice required to be properly handled. Hence, a non-deterministic optimization model based on information gap decision theory (IGDT) is proposed in this paper to specify a robust PEV smart charging pattern. To solve the multi-objective proposed IGDT-based PEV smart charging (IGDT-PSC) model, the multi-objective version of particle swarm optimization (MOPSO) is utilized to define a set of Pareto optimal solutions. Furthermore, the final solution among the Pareto solutions is selected by means of a linear fuzzy satisfaction rule. The simulation results for a test smart microgrid comprising a PEV, a set of RES units and a load demand verify the effectiveness of the proposed IGDT-PSC model.

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NOMENCLATURE

TC	Cost of purchased electrical energy ($).	CS_{int}/CS_{fin}	Initial/final charging state of the plug-in electric vehicle battery (%).
φ^t	Set of hours in a day (i.e. {0,1,..,24}).	γ_{ch}/γ_{dch}	Charging/discharging efficiency of the plug-in electric vehicle battery (%).
UP_t	Upstream power supplied by the main grid at hour *t* (kW).	$P^{PEV}_{ch,t}/P^{PEV}_{dch,t}$	Charging/discharging power of the plug-in electric vehicle battery at hour *t* (kW).
EP_t	Electrical energy price at hour *t* (Cent/kWh).	CS_t	Charging state associated with the plug-in electric vehicle battery at hour *t* (%).
LD_t	Load demand at hour *t* (kW).	CS^{min}/CS^{max}	Lowest/highest charging state value (%).
P_t^{PV}	Output power of the photovoltaic system at hour *t* (kW).	α_t/β_t	Binary variables showing the charging/discharging status of the plug-in electric vehicle battery at hour *t*.
P_t^{WT}	Output power of the wind turbine at hour *t* (kW).	$P^{max}_{ch}/P^{max}_{dch}$	Maximum permissible charging/discharging power of the plug-in electric vehicle battery (kW).
P_t^{PEV}	output power of the plug-in electric vehicle at hour *t* (kW).	$SE^{PEV}_{min}/SE^{PEV}_{max}$	Minimum/maximum value of the stored energy in the plug-in electric vehicle battery. (kWh).
E^{PEV}_{max}	Rated capacity of the plug-in electric vehicle (kWh).	RP	Robustness controlling parameter used in information gap decision theory.
E_t^{PEV}	Remained energy of the plug-in electric vehicle battery at hour *t* (kWh).	$\mu_{(o)}$	Boundry value related to *rz* of the uncertain variable (o).
$rz_{(o)}$	Robust zone associated with the uncertain variable (o).	δ	A user-defined value between 0 and 1 controlling the selection pressure of the leader associated with each cell.

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LD_t^{exp}	Expected value of the load demand at hour t (kW).
EP_t^{exp}	Expected value of the electrical energy price at hour t (Cent/kWh).
$P_t^{PV,exp}$ / $P_t^{WT,exp}$	Expected value of the photovoltaic/wind turbine output power at hour t (kW).
VE_k / PS_k	Velocity/position of the particle k.
GBT^{iter}	The best position ever discovered among the population until itertion *iter*.
PBT_k^{iter}	Best position arisen for the particle k until itertion *iter*.
c_1, c_2	Two predefined weighting factors regulating the moving step toward the particle's best position ever discovered and the best position ever discovered among the population, respectively.
r_1, r_2	Two random values with uniform distribution lying in the range of (0,1).
Greek Symbols	
λ	Inertial coefficient representing the particle's tendency to move along the previous position.
τ	A user-defined value between 0 and 1 controlling the selection pressure of the cell elimination.
Δt	Time step (h).
Subscripts	
t	Hour.
k	Number of candidate solution in particle swarm optimization.
ch / dch	Related to the charging/decharging.
i	Related to the number of each objective function.
n	Related to the number of each Pareto optimal solution.
ld / pv	Related to the load demand/photovoltaic unit.
wt / pr	Related to the wind turbine/electrical energy price.

1. INTRODUCTION

Green-house gases emission and so human health concerns, shortage and low accessibility of fossil fuel as well as its increasing price in world markets, low operation costs and also using the potential of energy storage are of the main techno/economic/enviromental incentives of the PEV application. The essential flexibility of the PEVs in both performance modes of electrical source/load has recently absorbed the attention of academic and industrial individuals to more investigate and exploit the operational advantages of such technology in modern power systems [1, 2]. At the same context, the extensive potential of RESs such as photovoltaic (PV) units, wind turbine (WT) units, fuel cells, geothermal energy, battery energy storage system (BESS), etc., as supportive low-emission cost power sources has been growingly taken into consideration in smart distribution grids [3-5]. In this way, the helpful role of PV/WT units in charging a PEV battery specifically in off-peak electrical energy prices can potentially lead to reduction in operation costs. At the same context, the valuable feature of battery discharging throughout the peak load interval of the main grid, aiming to more reduction of the operation costs, can further highlight the beneficial aspects of the PEVs [6]. Hence, based on contributory partnership of the PV/WT units, this paper concentrates on presenting a reasonable cost-effective PEV charging/discharging framework (called hereafter PEV smart charging (PSC)) in order to achieve the techno/economical purposes of all participants. In general, the main participants of PEV-equipped smart grids are PEV user (driver), grid operator and charging station owner. Thus, the PEV charging/discharging optimization can be variously implemented based on each of participants' interest. Load balancing, peak load shaving, cost minimization are among the main expectation of the grid operator from the smart PEV charging approach [7, 8]. On the other hand, the owner of charging station essentially seeks to earn more revenue from injecting (selling) the PEVs' stored energy especially within the peak price period. Without loss of the generality, the grid operator and the charging station owner is assumed to be identical in this paper. At this condition, the main target of the formulated PSC model is to sufficiently supply the load demand by focusing on reduction in total cost as much as possible. Additionally, the PEV user's interest is an important issue less emphasized in the recent research works. Based on this issue, in this paper, a comprehensive PSC model is proposed wherein the whole participants' desire are simultaneously taken into account. To incorporate the key role of the PEV user, the presented PSC model permits the PEV user to previously announce his/her desired arrival and departure time to/from the charging station as well as the interested initial and final charging state (*CS*) pertaining to the PEV battery. The data transmission infrastructure is practically provided by wireless communication technology employing the specialized applications installed at smart phones, etc. In this regard, immediately after receiving the required data of PEV user, the grid operator/charging station owner seeks to optimize the PEV terminal power (i.e. charging/discharging pattern) along a day considering all other relevant inputs including the load, PV/WT generation profiles as well as the economic data and constraints associated with both grid and PEV. Subsequently, the PEV user is informed from the optimization result (i.e. variation trend of the PEV terminal power) based on the technical specifications he/she announced before arrival to the charging station.

On the other hand, the load demand, PV/WT generation and also the electrical energy price are intrinsically exposed to the uncertainty in real-world smart grids, which has not been considered in the literature. In this way, to ensure a reliable and robust decicison outputs hedged against the uncertain characteristics of the mentioned parameters, an efficient uncertainty modeling approach should be utilized. Generally speaking, the well-known probabilistic [9-11] and possibilistic methods [12-14] are usually observed in recent research works to model the various uncertainty resources. In the former, the probability distribution function (PDF) of the uncertain variables is mandatory while the latter characterize the uncertain resources via their membership function. However, each of these two methods encounter with functional challenges somehow. Within the probabilistic methods, the PDF of some uncertain variables are not available or the uncertain variables do not follow any definite PDF. Moreover, in some cases, sufficient previously recorded data is not available to constitute an accurate PDF. On the other hand, the membership function is structurally formed according to the prior experience of the expert system, which is generally a non-trivial task in practice. Therefore, in this paper, the notion of IGDT is utilized to handle the uncertainty resources of the load, PV/WT generation and electrical energy price within the proposed PSC model. Two distinguished advantages of the IGDT versus the probabilistic/possibilistic methods can be enumerated. The first is the proficient performance of the IGDT under the least or no historical data about the past of uncertainty resources. Also, the second advantage is presenting a robust optimization outputs all protected against the worst fluctuation of the uncertain variables varying within their own robust zones [15-17]. Within the formulated IGDT-PSC model, the four uncertain variables including the load, PV/WT generation and electrical energy price competitively try to extend their relevant robust zones. Since these uncertain parameters are fundamentally heterogeneous, thus, the suggested non-deterministic IGDT-PSC model is in the form of a multi-objective optimization problem. To solve this problem, the multi-objective variant of PSO (i.e. MOPSO) is utilized to create a set of non-dominated Pareto solutions. Finally, to reach the best compromise solution among the Pareto solutions generated by the MOPSO, a well-known fuzzy-based satisfaction rule is employed.

The main contributions of this paper are as follows: 1) an IGDT-PSC model is proposed considering four uncertainty resources of load, PV/WT output and also electricity price; 2) the proposed model is comprehensive such that the techno-economic interests of all participants, i.e. the PEV user, grid operator and charging station owner, are concurrently met. To assess the effectiveness of the formulated IGDT-PSC model, it is implemented on a small-scale microgird including an electrical load, a set of PV/WT generation units and also a PEV. The simulation results including the daily profiles of the PEV terminal power (and so it's *CS*) is optimally calculated by simultaneous application of the proposed IGDT-PSC model, MOPSO and fuzzy-based satisfaction rule.

The rest of the paper is categorized as follows. In section 2, the suggested mathematical representation of the proposed deterministic PSC (DPSC) model is presented. The IGDT definition, the mathematical formulation of the proposed IGDT-PSC model, the MOPSO performance in creation of the non-dominated solutions and ultimately the fuzzy decision-making strategy is presented in section 3. Section 4 includes the simulation results obtained by simultaneous application of the proposed IGDT-PSC model, MOPSO and fuzzy-based rule aiming to specify the robust PEV charging/discharging scheme. Section 5 highlights the conclusion remarks.

2. THE PROPOSED DPSC MODEL

In this section, the mathematical formulation of the proposed DPSC model together with the associated technical constraints is presented.

2. 1. The Objective Function of the Proposed DPSC Model

The DPSC framework presented in this research work aims to minimize the daily cost of the electrical power procured from the main grid. In this regard, the mathematical representation of the suggested DPSC model specifying the optimal daily trend of the PEV terminal power (and so the pertinent *CS*) can be depicted as follow:

$$DOF = min\ TC \tag{1}$$

$$TC = \sum_{\forall t \in \varphi^t} (UP_t \times EP_t) \tag{2}$$

where *TC* denotes the electrical energy purchase cost. As illustrated in Equation (1), the main goal of the proposed DPSC model is to adequately meet the load power based on the minim *TC* imposed to the grid operator.

2. 2. Constraints

The following equality/inequality constraints, realted to both PEV battery and the main grid, are incorporated into the proposed DSPC model:

• Power balance should be satisfied all the day:

$$UP_t = LD_t - P_t^{PV} - P_t^{WT} - P_t^{PEV} \quad \forall t \in \varphi^t \tag{3}$$

$$P_t^{PEV} = (CS_t - CS_{t-\Delta t}) \times (\frac{E_{max}^{PEV}}{\Delta t}) \quad \forall t \in \varphi^t \tag{4}$$

By Comparing CS_t and $CS_{t-\Delta t}$ as well as assuming Δt=1h, three performance statuses for a PEV is defined as below:

$$\begin{cases} CS_t > CS_{t-1}; & charged \\ CS_t < CS_{t-1}; & discharged \\ CS_t = CS_{t-1}; & no\ \ operation\,(idle) \end{cases} \quad \forall t \in \varphi^t \tag{5}$$

• The variation trend of CS for the PEV battery during the time period between entering/leaving the charging station is determined by Equations (6)-(8). Furthermore, the time-based remaining energy of the PEV battery is calculated via Equation (9):

$$CS_{t \le AT} = CS_{int} \tag{6}$$

$$CS_{t \ge DT} = CS_{fin} \tag{7}$$

$$CS_{(AT < t < DT)} = CS_{(t-1)} + \left(\frac{E_t^{PEV}}{E_{max}^{PEV}} \right) \quad \forall t \in \varphi^t \tag{8}$$

$$\begin{aligned} E_t^{PEV} &= P_t^{PEV} \times (\Delta t = 1hr) \\ &= \gamma_{ch} \times P_{ch,t}^{PEV} - \left(\frac{P_{dch,t}^{PEV}}{\gamma_{dch}} \right) \quad \forall t \in \varphi^t \end{aligned} \tag{9}$$

• The functional restriction imposed to the charging/discharging rate, CS and stored energy of the PEV battery (affirmed by the manufacturer to prevent the loss of battery lifetime) is represented as follows:

$$P_{ch,t}^{PEV} \le \alpha_t \times P_{ch}^{max} \quad \forall t \in \varphi^t \tag{10}$$

$$P_{dch,t}^{PEV} \le \beta_t \times P_{dch}^{max} \quad \forall t \in \varphi^t \tag{11}$$

$$\alpha_t + \beta_t \le 1 \quad \forall t \in \varphi^t \,;\, \alpha_t, \beta_t \in \{0,1\} \tag{12}$$

$$CS^{min} \le CS_t \le CS^{max} \quad \forall t \in \varphi^t \tag{13}$$

$$SE_{min}^{PEV} \le E_t^{PEV} \le SE_{max}^{PEV} \quad \forall t \in \varphi^t \tag{14}$$

$$SE_{min}^{PEV} = CS^{min} \times E_{max}^{PEV} \quad \forall t \in \varphi^t \tag{15}$$

$$SE_{max}^{PEV} = CS^{max} \times E_{max}^{PEV} \quad \forall t \in \varphi^t \tag{16}$$

3. THE PROPOSED IGDT-PSC MODEL

In this section, the notion of IGDT as the uncertainty handling approach employed in this paper is firstly described in subsection 3.1. Afterwards, the mathematical formulation of the proposed IGDT-PSC model is presented in subsection 3.2. Since the IGDT-PSC model is a multi-objective optimization problem, the evolution procedure of the multi-objective PSO (MOPSO), utilized for solving the suggested model, is presented in subsection 3.3. Eventually, the fuzzy satisfaction-based decision rule used to select the best solution between the Pareto optimal solutions, created by the MOPSO, is elucidated in subsection 3.4.

3. 1. The Information Gap Decision Theory (IGDT)

In real-world power systems, the planning/operation process encounter with several economic/technical uncertainties. To model such uncertainty resources, the familiar probability distribution function (PDF) [9-11] for probabilistic approaches and fuzzy membership function [12-14] for possibilistic techniques have been recurrently employed in recent studies. Nevertheless, the PDF of the uncertain variables is not reachable or not appropriate for precise uncertainty modeling in most practical cases. Furthermore, the altering behaviour pertaining to some other uncertain variables does not follow a definite PDF. On the other hand, a fuzzy membership function requires the preceding skills of the expert individuals that are not available in some circumstances. Accordingly, a worthwhile uncertainty characterizing approach like IGDT can be an advantageous tool to cope with such uncertainty resources.

The main goal of the IGDT is to maximize the robustness of the decision outputs in a non-deterministic optimization problem. Within the IGDT, the permissible variation of the uncertain variables from their expected values is circumscribed to a boundary parameter namely robust zone. Based on this issue, IGDT attempts to maximize the toleration of the decision-making strategy versus any probable value realized for the uncertain variables throughout their own robust zones [15-17]. In other word, the robust solution achieved by the IGDT is secure against the worst-case deviation of the uncertainty resources all over their own robust zones.

Mathematically speaking, not surpassing the objective function of the non-deterministic problem from a predefined value is defined as the robustness of the decision-making procedure. The predefined value is the numerical value of the objective function associated with the related deterministic problem where no uncertainty resource is incorporated.

There are numerous methods to represent the variation behaviour of the uncertainty resources within the IGDT technique. The envelope bound is used in this paper for this purpose [18-20]. Let assume an optimization problem wherein X and Y denote the set of decision and uncertain variables, respectively. Considering the boundary value of μ, the envelope bound method characterizing the robust zones of the Y (i.e. rz) can be illustrated as follows:

$$Y \in rz\,(\mu, Y^{exp}) \tag{17}$$

$$rz\,(\mu, Y^{exp}) = \left| \frac{Y - Y^{exp}}{Y^{exp}} \right| \le \mu \tag{18}$$

where Y^{exp} is the expected (forecasted) value of the Y. According to Equation (18), the Y members can freely change within their own rz interval, confined by μ, as below:

$$(1-\mu)Y^{exp} \le Y \le (1+\mu)Y^{exp} \tag{19}$$

The chief role of the IGDT is to maximize the robust zone μ aiming to achieve a set of decision variables X immunized against any possible fluctuation of the Y members within their own robust zones representd in Equation (19). To better insight, consider $f^*(X,Y)$ as the numerical value of the non-deterministic objective function. Since more deviation of the Y members from their own expected values results in escalating the $f^*(X,Y)$, the highest value of $f^*(X,Y)$ to confirm the maximum robustness befalls when all Y members reach to their own upper bounds (i.e.$Y=(1+\mu).Y^{exp}$). Hence, the IGDT trying to attain the most extended rz for the set of Y can be mathematically formulated via Equations (20)-(22):

$$\max_X \; \mu(X, f(X)) \tag{20}$$

$$Y \in rz(\mu, Y^{exp}) \tag{21}$$

$$f^*(X, (Y=(1+\mu)Y^{exp})) \leq (1+UB).f(X) \tag{22}$$

where UB is a selective limiting value predefined by the decision-maker. The UB value is directly relies on the decision-maker prospect such that how much robustness, as shown in Equation (22), is desired to realize.

3. 2. Mathematical Representation of the Suggested IGDT-PSC Model The DPSC model developed in section 2 is exposed to the multifold uncertainties in practical environment. As explicated beforehand, the uncertainty resources of this paper comprise the load demand, PV/WT output power, and also the electrical energy price which should be incorporated into the DPSC model given in Equations (1)-(16).

To mathematically formulate the IGDT-PSC model, the set of decision variables (X), uncertain variables (Y), robust zones (rz), and boundary enveloping values (μ) are considered as follow:

$$X = \left\{\alpha_t, \beta_t, P_t^{PEV}\right\} \tag{23}$$

$$Y = \left\{LD_t, P_t^{PV}, P_t^{WT}, EP_t\right\} \tag{24}$$

$$rz = \left\{rz_{ld}, rz_{pv}, rz_{wt}, rz_{pr}\right\} \tag{25}$$

$$\mu = \left\{\mu_{ld}, \mu_{pv}, \mu_{wt}, \mu_{pr}\right\} \tag{26}$$

Based on Equation (18), the set of rz assoicted with the four uncertainty resources of the proposed IGDT-PSC model can be illustrated as follows:

$$rz_{ld} = \left|\frac{LD_t - LD_t^{exp}}{LD_t^{exp}}\right| \leq \mu_{ld} \tag{27}$$

$$rz_{pv} = \left|\frac{P_t^{PV} - P_t^{PV,exp}}{P_t^{PV,exp}}\right| \leq \mu_{pv} \tag{28}$$

$$rz_{wt} = \left|\frac{P_t^{WT} - P_t^{WT,exp}}{P_t^{WT,exp}}\right| \leq \mu_{wt} \tag{29}$$

$$rz_{pr} = \left|\frac{EP_t - EP_t^{exp}}{EP_t^{exp}}\right| \leq \mu_{pr} \tag{30}$$

Considering Equations (27)-(30), the worst-case value of the uncertain variables are: $(1+\mu_{ld}).LD_t^{exp}$ for the load demand, $(1-\mu_{pv}).P_t^{PV,exp}$ / $(1-\mu_{wt}).P_t^{WT,exp}$ for the PV/WT output power and $(1+\mu_{pr}).EP_t^{exp}$ for the electrical energy price. Therefore, the extended form of the IGDT-PSC model can be mathematically demonstrated by Equations (31)-(35):

$$\begin{aligned} &max \;\; (\mu_{ld}, \mu_{pv}, \mu_{wt}, \mu_{pr}) \\ &s.t. \end{aligned} \tag{31}$$

$$\begin{aligned} ROF \equiv\; & TC(UP, CS, LD, P^{PV}, P^{WT}, EP, P^{PEV}) \\ & \leq (1+RP).DOF \end{aligned} \tag{32}$$

$$TC = \sum\nolimits_{\forall t \in \varphi^t} (UP_t.(1+\mu_{pr}).EP_t) \tag{33}$$

$$\begin{aligned} UP_t = (1+\mu_{ld}).LD_t - (1-\mu_{pv}).P_t^{PV} - \quad & \forall t \in \varphi^t \\ (1-\mu_{wt}).P_t^{WT} - P_t^{PEV} & \end{aligned} \tag{34}$$

Equations (3) to (16) (35)

It is evident that the proposed IGDT-PSC model presented in Equations (31)-(35) is characteristically a multi-objective optimization problem. The MOPSO algorithm is employed to solve this model and so generate a set of Pareto optimal solutions. In the following, the step-by-step performance of MOPSO is described.

3. 3. Multi-objective Particle Swarm Optimization (MOPSO) In the following, the original PSO is briefly reviewed in subsection 3.3.1. Then, the dominance theory raised in multi-objective optimization problems is mathematically elucidated in section 3.3.2. Finally, the step-by-step evolutionary performance of the MOPSO is described in section 3.3.3.

3. 3. 1. Brief Description of the Original PSO The original PSO inspires from group movement of the fishes/birds herd (population). This metaheuristic optimization algorithm and also its enhanced variants have been numerously utilized in recent power system problems [21-24]. In original PSO, each member of the population (i.e. each candidate solution) is generally known as a particle which can be iteratively evolved by means of adaptive movement toward two other positions in the feasible search space. The first is the best position arisen for each particle (PBT) and the second is the best position ever discovered among the population (*GBT*). To mathematically represent the chronological movement of each PSO particle, consider an optimization problem with *m* decision variables. The velocity and position of the particle *k* can be respectively indicated by Equations (36) and (37):

$$VE_k = [ve_k^1, ve_k^2, ..., ve_k^m] \tag{36}$$

$$PS_k = [ps_k^1, ps_k^2, ..., ps_k^m] \tag{37}$$

Thus, the iterative update for both VE_k and PS_k is as follows:

$$\begin{aligned} VE_k^{iter+1} &= \lambda.VE_k^{iter} + c_1.r_1.(PBT_k^{iter} - PS_k^{iter}) + \\ & c_2.r_2.(GBT^{iter} - PS_k^{iter}) \qquad k \in \{1,2,...,N_{sol}\} \end{aligned} \tag{38}$$

$$PS_k^{iter+1} = PS_k^{iter} + VE_k^{iter+1} \tag{39}$$

where N_{sol} and *iter* are respectively symbolized for the number of particles and counter of PSO iterations. Furthermore, c_1 and c_2 are two predefined weighting factor regulating the moving step toward the particle's *PBT* and population's *GPT*, respectively (classically c_1+c_2 =4 [21-24]). The inertial coefficient λ depicts the particle's tendency to move along the previous position. In general, this factor is initialized with a high value and gradually drops to the lower values along with the PSO iterations. Ultimately, r_1 and r_2 are two random values with uniform distribution lying in the range of (0,1).

The update approach of Equations (38)-(39) is iteratively replicated up to the termination condition (i.e. reach to the maximum iteration number). The *GBT* in the last iteration ($iter_{max}$) is designated as the PSO best solution.

3. 3. 2. Dominance Theory A multi-objective optimization problem with *u* decision variable and *nb* objective functions can be mathematically demonstrated as follows (without loss of the generality, a maximization problem is taken into account):

$$F(X) = [f_1(X), f_2(X), ..., f_{nb}(X)] \tag{40}$$

$$X = [x_1, x_2 ..., x_u] \tag{41}$$

$$EC(X) = \bar{0}\ , \ \ IC(X) \le \bar{0} \tag{42}$$

where *EC*(*X*) and *IC*(*X*) are clique of the equality and inequality constraints, respectively. If X_1 and X_2 are two feasible candidate solutions, X_2 is dominated by X_1 when the following conditions are concurrently fulfilled:

$$\forall i \in \{1,2,...,nb\} \Rightarrow f_i(X_1) \ge f_i(X_2) \tag{43}$$

$$\exists i' \in \{1,2,...,nb\} \Rightarrow f_{i'}(X_1) \ge f_{i'}(X_2) \tag{44}$$

3. 3. 3. The MOPSO Step-By-Step Algorithm Compared with original PSO, the *GBT* is replaced by the notion of "leader" selected among a set of non-dominated solutions (namely Pareto optimal solutions) in every iteration of the MOPSO. Moreover, the mentioned Pareto solutions are stockpiled in a specific archive known as "repository". Accordingly, the step-by-step algorithm of MOPSO aiming to generation of non-dominated solutions (repository members) can be elucidated as follows [25, 26]:

1. A predefined number of initial candidate solutions (population) are created with respect to allowable range of the decision variables as well as problem constraints.
2. Compute the values of all the objective functions for every particle. The *PBT* for each particle is the same as generated in the previous step.
3. Based on the dominance theory introduced in section 3.3.2, a certain number of particles are specified as the non-dominated (Pareto) solutions and then keep them in the repository.
4. A leader among the repository members is selected for every particle. For this purpose, the Pareto frontier made by MOPSO is divided to a number of adjoining cells using the grid constitution presented by Sepehrzad et al. [25]. In this case, assuming np_b as the number of repository members located in cell *b* (i.e. size of cell *b*), the leader selection probability associated with the cell *b* can be calculated based on Boltzmann function, as follows:

$$P_b^{sl} = \frac{\exp(-\delta.np_b)}{\sum_{np_j} \exp(-\delta.np_j)} \tag{45}$$

where δ is a user-defined value between 0 and 1 controlling the selection pressure of the leader associated with each cell. The less the cell size is, the more the probability of leader selection for that cell. Calculating the leader selection probability for all cells, one cell is accidentally selected for each particle based on Roulette Wheel method [27]. Subsequently, one member of the specified cell is randomly selected as the leader. The mentioned mechanism is repeated for all particles out of the repository.
5. For each particle, the velocity and position are evolved analogous to the method presented in Equations (38)-(39), respectively. The *GBT* in Equation (38) is substituted by the associated leader of the particle. The new *PBT* for each particle is dependent on the dominance condition between the previous *PBT* and the updated position of that particle. In this context, if the updated position dominates the previous *PBT*, the new *PBT* is switched to the updated position; otherwise, the *PBT* remains unchanged. If none of the updated position and previous *PBT* can dominate each other, the new *PBT* is randomly determined among them.
6. Investigate the dominance status for the updated particles and then add the non-dominated particles to the

repository of the preceding iteration. The updated repository is checked and so the dominated members are eliminated.

7. If the number of repository members surpasses a definite value, the excessive members should be discarded. Thus, the Boltzmann operator of Equation (45) is transformed to Equation (46) in this condition with the aim of calculating the elimination probability for cell b (P_b^{ce}):

$$P_b^{ce} = \frac{\exp(-\tau.np_b)}{\sum_{np_j} \exp(-\tau.np_j)} \tag{46}$$

where τ (another real value in the interval (0,1)) controls the selection pressure of the cell elimination. Likewise the approach in step 4, one cell is stochastically selected and then, one of its members is randomly removed. However, opposed to the step 4, the more the size of a cell is, the more the probability of selection for removing the associated members. The removing procedure is continued till the repository size comes back to the pre-allocated value.

8. Check the stopping condition as realization of the $iter_{max}$. If true, the last residual members of the repository are reported as the best found Pareto optimal solutions. Otherwise, return to the step 4.

3. 4. Fuzzy-Based Satisfaction Rule

To select the final solution amongst the set of Pareto solutions created by the MOPSO, a linear fuzzy rule is utilized. This approach is commonly employed while no preference/priority between the objectives is considered [28]. Based on Equations (43)-(44) and also the lettering of section 3.3.2, the fuzzy value $(\vartheta_{X_n}^{f_i})$ is computed for Pareto solution X_n as below:

$$\vartheta_{X_n}^{f_i} = \begin{cases} 1 & f_i(X_n) > f_{i,max} \\ \dfrac{f_i(X_n) - f_{i,min}}{f_{i,max} - f_{i,min}} & f_{i,min} \le f_i(X_n) \le f_{i,max} \\ 0 & f_i(X_n) < f_{i,min} \end{cases} \tag{47}$$

where $f_{i,min}$ and $f_{i,max}$ are the lowest and highest value of the f_i. Considering N_{pb} as the number of Pareto solutions, the X_n having the maximum $\vartheta_{X_n}^{f_i}$ is identified as the final solution using the following selective max-min function:

$$\max_{n=1:N_{pb}} \min_{i=1:nb} \vartheta_{X_n}^{f_i} \tag{48}$$

4. SIMULATION RESULTS

In this section, the input data used for the simulation process are first presented in subsection 4.1. In the following, subsection 4.2 includes the numerical results obtained by application of the proposed IGDT-PSC, MOPSO and the fuzzy satisfaction method on a test micro smart grid. Finally, subsection 4.3 presents a kind of comparative results aiming to appraise the robustness of the suggested IGDT-PSC model based on different values of *RP*.

4. 1. Data Used for the Simulation Study

To analyze the efficiacy of the suggested IGDT-PSC model in terms of specifying a robust techno-economic scheme for the PEV smart charging, a test microgrid shematically depicted in Figure 1 is considered. As demonstrated in Figure 1, the test microgrid comprises a load demand, a set of PV/WT units and a PEV. The variation trend of the load demand, PV/WT generation and electrical energy price are depicted in Figures 2 and 3, respectively. The descriptive data related to the PEV (with maximum power of 3.5 kW) and PV/WT units are presented in Table 1. It is assumed that the PEV arrives the charging staion at 4:00 by CS_{int}=0.4 and leave there at 23:00 by CS_{fin}=0.8. Moreover, CS^{min} and CS^{max} are supposed to be 0.2 and 0.9, respectively. The tunable parameters of the MOPSO are depicted in Table 2. Moreover, the computational coding associated with the proposed IGDT-PSC model, the MOPSO and the fuzzy satisfaction approach are all implemented in MATLAB 7.5 software. Additionally, the hardware package utilized for the execuation of the simulations consists of a PC equipped by a core™ i5 2.3 GHz CPU and also a 4 GB RAM.

4. 2. Numerical Results for the Test Microgrid

In the proposed IGDT-PSC model solved through MOPSO, the profiles of Figures 2 and 3 including the load power, PV power, wind power and the electrical

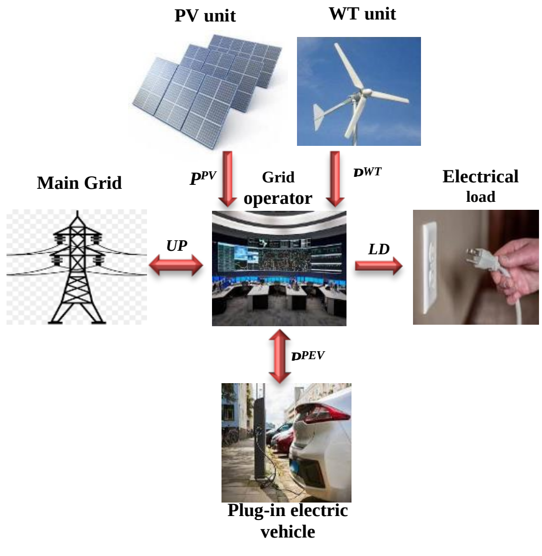

Figure 1. The shematic illustration of the test microgrid used for the simulation studies

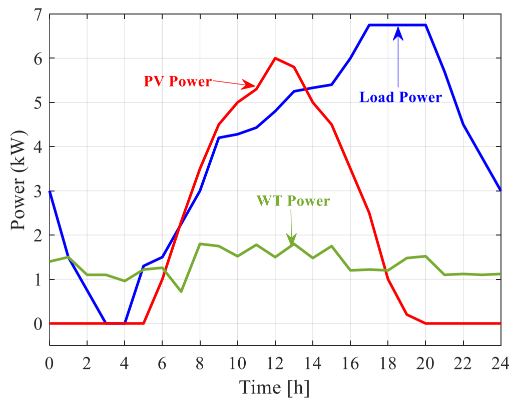

Figure 2. The daily profile of load power, PV power, and WT power

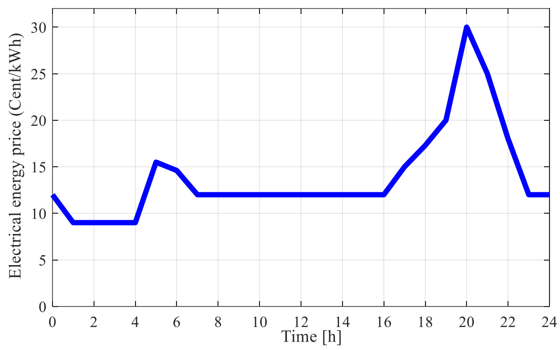

Figure 3. The daily profile of electrical energy price

TABLE 1. The descriptive data of PEV and PV/WT units

List of data	Value
P_{max}^{PV} (rated power of PV unit)	7 kW
P_{max}^{WT} (rated power of WT unit)	2 kW
P_{ch}^{max} / P_{dch}^{max}	-3.5/+3.5 kW
E_{max}^{PEV}	24 kWh

TABLE 2. Tunable parameters of the MOPSO

List of tunable parametrs	Assigned values
Number of population	80
Maximum number of repository members	20
$Iter_{max}$	100
δ, τ	0.4
C_1,C_2	2

energy price should be taken into account for analyzing the numericals results pertaining to the test microgrid. This analysis encompasses the results associated with the optimal daily profiles of the grid power, PEV power, and the *CS* of PEV all demonstrated in Figures 4 and 5 for *UB*= 0.25 and *UB*= 0.75, respectively. It is seen from Figures 2 and 3 that within the interval of maximum PV/WT generation wherein the electrical energy price remains constant, the proposed IGDT-PSC enables the PEV to be persistently charged for both *UB*=0.25 and *UB*=0.75.

However, comparing the obtained results of the PEV power for the cases of *UB*=0.25 and *UB*=0.75, it can be realized that the proposed robust optimization strategy can force the PEV to be more in charging mode in the case of *UB*=0.25. Nevertheless, during this operating status, the *CS* of PEV would possess its maximum values according to Figures 4(a) and 5(a). Within the interval of RESs' maximum generation, the moderate level of load consumption is also devoted in which the grid power is appointed to provide the load demand despite the RESs' generation for both *UB*=0.25 and 0.75.

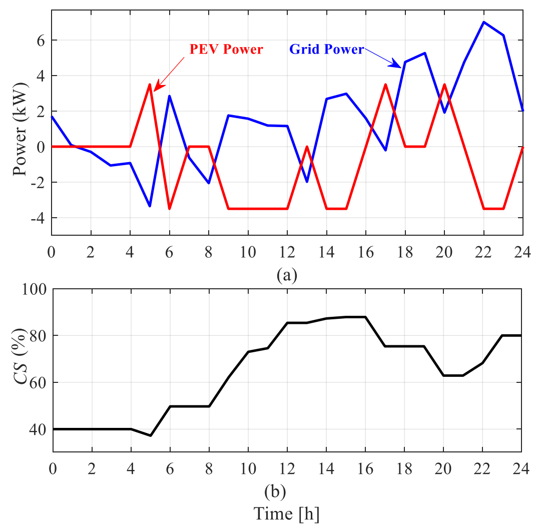

Figure 4. (a) PEV and grid power, (b) *CS*, all for *UB*=0.25

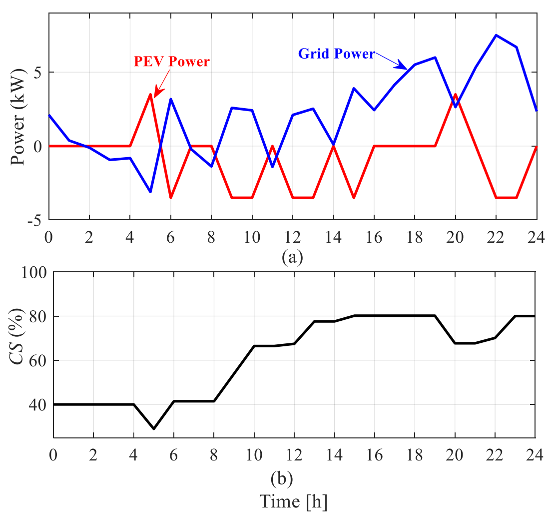

Figure 5. PEV and grid power, (b) *CS*, all for *UB*=0.75

Since the electrical energy price is increased throughout the interval [19h, 22h] with its top value at t=20h, the proposed strategy causes optimal PEV discharging especially at t=20h for both UB=0.25 and 0.75, as exhibited in Figures 4(a) and 5(a), respectively. It is worth mentioning that the PEV is kept in discharging mode for UB=0.25 more than UB=0.75. Within the interval [19h, 22h], the CS of PEV experiences a significant drop that must be compensated to attain its desired value at the departure time leading to the charging mode activation of the PEV, as seen from both Figures 4(b) and 5(b). In this condition, the grid power (with relatively high value) along with the WT unit are responsible for supplying the load demand and PEVcharging power.

4. 3. Comparative Results This section firstlty evaluates the variation trend of envelope bounds {μ_{lp}, μ_{pv}, μ_{wt}, μ_{pr}} while the UB value is increased accordingly. As it is expected, Figure 6 verifies that the higher value of UB causes a larger envelope bounds demonstrating a further robustness feature. In this way, the most robustness feature for each envelope bound is belong to UB=1. Among the envelope bounds, the minimum and maximum increments are respectively achieved for μ_{lp} and μ_{pr} wherein the μ_{pr} has the most increment from zero to 0.25. Moreover, when the UB value is increased from 0.5 to 0.75, three envelope bounds {μ_{lp}, μ_{wt}, μ_{pr}} encounter relatively high augmentation as depicted in Figure 6 validating a significant enhancement on the robustness of the proposed IGDT-PSC. However, it is worth noting that the least increment occurs for μ_{pv} while the UB is changed from 0.5 to 0.75. Figure 7 illustrates the results of the ROF and also ROF-DOF (as a robustness indice) obtained from the proposed IGDT-PSC model for disparate UB values of {0, 0.25, 0.5 ,0.75, 1}. When the UB is changed from 0 to 0.25, the ROF approaches approximately three times more than its initial value. Despite this noticeable ascent, there is only \$50 difference between the ROF values associated to UB=0.25 and UB=0.5 as observed in Figure 7.

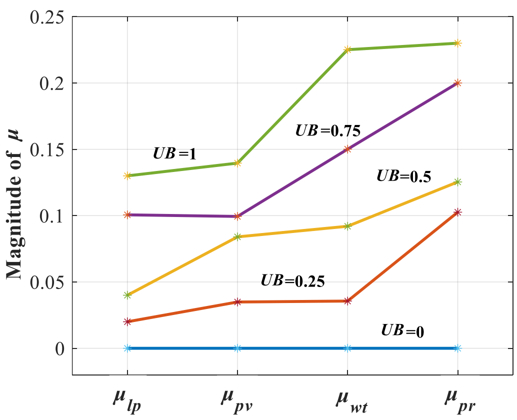

Figure 6. The alteration trend of envelope bounds considering various UB

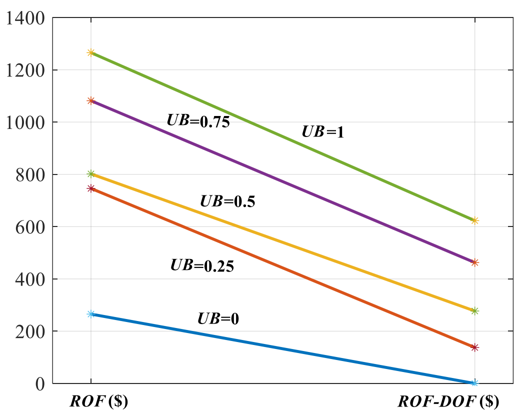

Figure 7. The alteration trend of ROF and ROF-DOF considering various UB

5. CONCLUSION

In this paper, a robust deicion-making framework for the PEV smart charging in a RES-oriented microgrid is suggested. The RESs including PV and WT units are utilized to collaboratively participate in the PEV charging strategy along a day. On the other hand, the proposed model is exposed to intrinsic uncertainty in practice. The daily profiles of load demand, output power of the PV/WT units as well as the electrical energy price are of the essential uncertainty recourses which should be inevitably integrated with the proposed model. Since the mentioned uncertainty resources have low-frequency nature, the well-known IGDT technique is utilized to characterize their fluctuating/unpredictable behaviour. Regarding the hetergenous features of the uncertainty resources as well as the restricted ROF value (controlled by predefined UB), the formulated IGDT-PSC model is a muti-objective optimization problem. Hence, the MOPSO algorithm is utilized to solve this model. Subsequently, the final solution (i.e. optimal envelope bound of the robust zone associated to every uncertain variable) amongst the set of Pareto solutions is determined using a linear max-min fuzzy-based rule.

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Persian Abstract

چکیده

امروزه مفهوم خودروهای برقی به عنوان یک ابزار ارزشمند مدیریت انرژی به طور وسیعی در شبکه‌های توزیع هوشمند به کار گرفته شده است. مزیت عمده انرژی پاک و همچنین عملکرد انعطاف‌پذیر خودروهای برقی در هر دو حالت تولیدی/ مصرفی می‌تواند به اندازه کافی استفاده از این فناوری‌های نوظهور را توجیه نماید. علاوه بر این، ویژگی خاص منابع انرژی تجدیدپذیر در قالب مشارکت در برنامه شارژ/دشارژ هوشمند خودروهای برقی منجر به مزایای فنی- اقتصادی قابل توجهی در شبکه‌های هوشمند گردد. اما، تقاضای بار الکتریکی، تولید منابع تجدیدپذیر و همچنین قیمت انرژی الکتریکی با مقوله عدم قطعیت مواجه بوده که می‌بایست به طور مناسبی به آن رسیدگی گردد. به همین جهت، در این مقاله یک مدل بهینه‌سازی غیرقطعی بر پایه نظریه تصمیم‌گیری بر اساس شکاف اطلاعات به منظور تعیین یک برنامه مقاوم برای شارژ هوشمند خودروی برقی ارائه گردیده است. جهت حل مدل چندهدفه و مقاوم پیشنهادی، از نسخه چندهدفه الگوریتم بهینه‌سازی ذرات با هدف تولید یک گروه از پاسخ‌های بهینه نامغلوب (پارتو) استفاده گردیده است. همچنین، پاسخ نهایی از میان پاسخ‌های بهینه پارتو به کمک یک روش فازی خطی تعیین می‌گردد. نتایج شبیه‌سازی برای یک ریزشبکه هوشمند متشکل از یک خودروی برقی، یک گروه از منابع تجدیدپذیر و یک بار الکتریکی، اثربخشی مدل مقاوم پیشنهادی جهت شارژ هوشمند خودروی برقی را تایید می‌کند.