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Enhancing Hosting Capacity of Intermittent Wind Turbine Systems Using Bi-level Optimization Considering OLTC and Electric Vehicle Charging Stations

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Abstract: Worldwide, the hosting capacity of renewable energy sources (RES) is remarkably expanded in distribution systems. One of the most auspicious RES is wind turbine systems (WTSs), which can improve the performance of distribution systems. In turn, the integration of high WTS penetrations can also deviate the system operation away from the standard condition. To tackle this issue, we propose a method for enhancing the hosting capacity of multiple WTSs considering their intermittent generations in distribution systems. The proposed method considers the operation of the on-load tap changer (OLTC), allowing to solve voltage problems efficiently. Especially, the proposed method optimizes the charging/discharging power of electric vehicles (EVs), which can contribute positively to regulating WTS intermittent generation. Additionally, the reactive power support of WTSs, complying with the IEEE 1547:2018 standard, are incorporated in the planning model of WTSs. To solve such an optimization problem, a bi-level optimization algorithm is developed based on the gravitational search algorithm (GSA). Comprehensive simulation results are performed on the 69-bus distribution feeder interconnected to four EV stations. Based on the results, the proposed approach can efficiently enhance/increase the hosting capacity of WTSs in distribution systems, thanks to the consideration of OLTC, reactive power support of WTSs and EVs.

Nomenclature

$P_{WT,s}^t$	generated power of WT unit for the state s during time segment t	ϕ_b	set of the system buses
n_t	number of time segments	$S_{inv,i}$	inverter rating
n_s	number of the states	ϕ_r	set of the system branches
n_B	number of valid buses	tap^{min}	minimum tap position
n_k	number of WT units at bus k	tap^{max}	maximum tap position
λ	a matrix with two columns which comprises all possible amalgamations of WT power states and the load demand states	$P_{dc,n,s}^t$	discharging power of n^{th} EV
B_{ij}	susceptance of line ij	$P_{ch,n,s}^t$	charging power of n^{th} EV
G_{ij}	conductance of line ij	$\eta_{ch,n}$	charging efficiency of n^{th} EV
$V_{i,s}^t$	voltage magnitude at bus i	$\eta_{dc,n}$	discharging efficiency of n^{th} EV
$\delta_{ij,s}^t$	voltage angles variance at i^{th} and j^{th} nodes	$SOC_{n,d,s}$	SOC of n^{th} battery at departure time
$P_{d,i}^t$	load demand	$SOC_{n,min,s}$	minimum SOC set by the vehicle's owner
$P_{CS,j,s}^t$	charging station power	$SOC_{n,s}^t$	current SOC of n^{th} EV
n_b	number of nodes	$SOC_{n,s}^{t-1}$	previous SOC of n^{th} EV
$Q_{d,i}^t$	reactive power demand	$T_{arr,n}$	arrival time of n^{th} EV
$P_{cs,i,s}^{min,t}$	minimum charging station power	$T_{d,n}$	departure time of n^{th} EV
$P_{cs,i,s}^{max,t}$	maximum charging station power	$\mu_{T_{arr}}^t, \sigma_{T_{arr}}^t$	mean and standard deviation of daily arrival time
n_i^{min}	minimum allowed number of WT units at bus i	$C_{batt,n}$	capacity of the n^{th} EV
n_i^{max}	maximum allowed number of WT units at bus i	$E_{cons/mile,n}$	energy consumption per mile
$Q_{inv,i,s}^t$	reactive power of the interfacing inverter	$\mu_{dm}^t, \sigma_{dm}^t$	mean and standard deviation of daily mileage
$Q_{inv,i,s}^{max}$	highest reactive power at bus i	c	scale parameter
$Q_{inv,i,s}^{min}$	lowest reactive power at bus i	k	shape parameter
V^{min}	lowest voltage limit	μ_v, σ_v	mean and standard deviation of wind speed
V^{max}	highest voltage limit	$P_v^t(G_w)$	wind speed probability of state w
$V_{1,s}^t$	voltage at slack bus	v_{w1}, v_{w2}	wind speed lower and upper limits of state w
$\delta_{1,s}^t$	voltage angle at slack bus	v_{ci}	cut-in speed of the WT
		v_{co}	cut-off speed of the WT
		v_r	rated speed of the WT
		v_{avw}	wind speed average for state w
		P_{rated}	rated power of the WT
		$P_{WT_w}^t$	power output of WT unit
		$P_l^t(G_u)$	load demand probability of state u

l_{u1}, l_{u2}	load demand limits of state u
$P_{comb}^t(\lambda_s)$	amalgamated probability model of the wind speed and demand load
$fit_i(t)$	fitness value of i^{th} object at time t
$worst(t)$	worst fitness value of the objects at time t
N	number of objects
$G(t)$	gravity constant
$G_0(t)$	initial value

ε	very small value
r_i, r_j	two random numbers in the range $[0,1]$
$R_{ij}(t)$	Euclidian distance between object i and object j
$v_i^d(t)$	velocity of the object at time instant t in the dimension d
$x_i^d(t)$	position velocity of the object at time instant t in the dimension d
α	a user-specified constant term

1. Introduction

Installing wind turbine systems (WTSs) in the electric power network has shown significant growth driven by environmental and economic aspects. This rising trend is predicted to continue or even been accelerated, which boosts research and development related to WTSs [1, 2]. In power systems, large-size WTSs are interconnected to transmission systems, while small-size WTSs are interconnected to distribution systems beside load hubs. It is a fact that WTSs can have positive influences on the grid, such as cost-saving, carbon emission reduction, supply reliability improvement, power loss reductions [3, 4]. In turn, the immense integration of WTSs into distribution feeders can disorder their normal operation state by causing various operational problems, such as voltage rise, voltage drop, inverse power flows, and increasing active and reactive losses in distribution lines. Such issues are often limit the allowed installed capacity of WTSs, which consider challengeable to distribution system planners. Accordingly, enhancing the hosting capacity (HC) of WTSs receives considerable attention lately in distribution systems.

Like WTSs, the number of electric vehicles (EVs) has been widely expanded worldwide. This trend is motivated by the development of the EV batteries and their declining cost tendency while installing sufficient charging stations interconnected to the grid [5, 6]. In [7], it is reported that the global number of EV trades was only 10K ones in 2010 while it increased to 774K in 2016 with almost 2M cumulative trades. Further, the electric vehicle initiative union has adopted an aspiration plan to increase the number of EVs to 20M in 2020 [8]. Grid-connected charging stations of EVs can have considerable impacts on the operation of distribution systems. Common benefits can be achieved by utilizing the energy exchange capability of the batteries of EVs, which can balance the fluctuated WTS generation and load demand [9, 10]. On the other side, these regulatory benefits cannot be fully attained when adopting the uncontrolled charging of EVs, thereby reducing the hosting capacity of WTSs.

Diverse methods have been proposed in the literature to enhance the hosting capacity of WTSs in distribution systems. In [11], the usage of active-management approaches has been introduced to increase the hosting capacity of WTSs in distribution systems. A probabilistic model has been proposed in [12] to determine the optimal capacity of WTSs, whereas the objective function is to reduce energy losses in distribution lines considering system constraints. Analytical based methods have been proposed in [13, 14] to determine the optimal sizes and locations of multiple WTSs at the nominal loading case. The authors of [15] have investigated the vital role of the reactive power support in enhancing the performance of distribution systems

integrated with renewables. To minimize energy losses and increasing the hosting capacity of WTSs, the authors of [16] have introduced an optimization-based method, and they have highlighted the effects of demand response on the hosting capacity of WTSs. An approach based on multi-objective has been suggested in [17] for the allocation of WTSs for lessening carbon emissions and operational costs. Various metaheuristic-based methods have been proposed for optimizing the capacity of WTSs in distribution systems, such as: cuckoo search algorithm (CSA) [18], particle swarm optimization (PSO) [19], grey wolf optimization (GWO) [20], and simulated annealing algorithm (SAA) [21]. In [22], the utilization of energy storage systems for increasing the hosting capacity of renewables has been investigated in distribution systems. In [23], the probabilistic HC approach of intermittent renewables in non-sinusoidal power distribution networks has been proposed. A stochastic approach for quantifying the HC of hybrid energy sources has been investigated in [24]. The authors of [25] have proposed a probabilistic-based approach to maximize the HC of renewables in radial distribution systems considering voltage rise and voltage deviation.

In this work, an approach is proposed to enhance the hosting capacity of multiple WTSs at various buses considering their intermittent generations and load variations in distribution systems. Unlike the existing methods, the proposed method optimizes charging the discharging power of EVs based on the adopted charging scheme, considering their stochastic behaviour. This procedure enhances the hosting capacity of WTS while satisfying the charging goal of EVs. Further, the operation of the on-load tap changer (OLTC) is considered, which regulates voltage effectively. The reactive power capability of WTSs is also incorporated in the planning model of WTSs, complying with the IEEE 1547:2018 standard. A bi-level optimization algorithm with inner and outer layers is proposed to solve such a complex optimization model. The role of the inner layer is to optimally adjust the EV charging/discharging power, reactive power of WTSs, and tap positions of OLTC. In turn, the hosting capacity of total WTSs is optimized in the studied distribution system by the outer layer. Since the proposed model is comprehensive and optimizes the various variables simultaneously, the hosting capacity of WTSs is significantly enhanced in distribution systems considering their pre-set operational constraints.

2. Problem description

WTSs are considered as non-dispatchable distributed generations in distribution systems whose power generation mainly depends on the wind speed. Accordingly, the variable generation of WTSs can introduce various technical problems into the hosting distribution system. For

Fig. 1. Schematic diagram of hosting capacity curves of WTSs.

example, voltage violations are common problems during high and low generations with high and low wind profiles, respectively. This limitation can significantly reduce the permissible installed capacities of WTSs in distribution systems, which is called the hosting capacity of WTSs. Fig. 1 describes the hosting capacity of WTSs in different scenarios. Specifically, the variation of an evaluation index (e.g. voltage) is investigated against the capacity of WTSs. In the base scenario that does not consider any control variable, the maximum hosting capacity of WTSs considering the index boundary between normal and up-normal condition has a small value. However, the hosting capacity of WTSs can be significantly increased when control variables are optimized. Here, we consider various variables: 1) OLTC operation, 2) EV charging schemes, and 3) WTS reactive power. As a result, the proposed method can increase the hosting capacity of WTSs in distribution systems.

3. Problem formulation

3.1. Objective function

The aim of this work is to enhance the hosting capacity of intermittent WTSs considering OLTC, reactive power capability of the interfacing inverters, and stochastic EVs. The optimization model uses two uncertain parameters, one of these parameters is the demand load while the other one is the generated power by WTSs. The injected active power from the WTSs for all possible amalgamation of the unpredictable parameters considering EVs is an objective function has to be maximized. The probability distribution function (pdf) of each unpredictable parameter (i.e., demand load and generated WTSs power) is divided into multiple states at each time instant t . The objective function can be mathematically expressed as follows:

$$\text{Max} \sum_{t=1}^{n_t} \sum_{s=1}^{n_s} \sum_{k=1}^{n_B} n_k P_{WT,s}^t \quad (1)$$

where $P_{WT,s}^t$ is the generated power of the wind turbine (WT) unit; n_t , n_s , and n_B are the numbers of time segments, number of states, and number of valid buses in the distribution system for installing WTSs, respectively; n_k is the number of WT units at bus k .

The following constraints (equality and inequality) are incorporated into the optimization problem.

$$\lambda(s, 1)n_i P_{WT,i}^t - \lambda(s, 2)P_{d,i}^t \pm P_{CS,i,s}^t -$$

$$V_{i,s}^t \sum_{j=1}^{n_b} V_{j,s}^t [G_{ij} \cos \delta_{ij,s}^t + B_{ij} \sin \delta_{ij,s}^t] = 0 \quad (2)$$

$$Q_{inv,i,s}^t - \lambda(s, 2)Q_{d,i}^t - V_{i,s}^t \sum_{j=1}^{n_b} V_{j,s}^t \text{tap}_{ij,s} [G_{ij} \sin \delta_{ij,s}^t + B_{ij} \cos \delta_{ij,s}^t] = 0, \forall i \notin \phi_b, s, t \quad (3)$$

$$V_{1,s}^t = 1.0, \delta_{1,s}^t = 0.0 \quad (4)$$

$$V^{min} \leq V_{i,s}^t \leq V^{max}, \forall i \in \phi_b, s, t \quad (5)$$

$$P_{cs,i,s}^{min,t} \leq P_{cs,i,s}^t \leq P_{cs,i,s}^{max,t}, \forall i \in \phi_b, s, t \quad (6)$$

$$n_i^{min} \leq n_i \leq n_i^{max}, \forall i \in \phi_b \quad (7)$$

$$Q_{inv,i,s}^{min,t} \leq Q_{inv,i,s}^t \leq Q_{inv,i,s}^{max,t}, \forall i \in \phi_b, s, t \quad (8)$$

$$\begin{cases} Q_{inv,i,s}^{max,t} = \sqrt{S_{inv,i}^2 - (P_{WT,i,s}^t)^2} \\ Q_{inv,i,s}^{min,t} = -\sqrt{S_{inv,i}^2 - (P_{WT,i,s}^t)^2} \end{cases} \quad (9)$$

$$\text{tap}^{min} \leq \text{tap}_{km}^t \leq \text{tap}^{max} \quad \forall (k, m) \in \varphi_r \quad (10)$$

$$\text{SOC}_{n,d,s} \geq \text{SOC}_{n,min,s} \quad (11)$$

where λ is a matrix with two columns which comprises all possible amalgamations of WT power states and the load demand states; B_{ij} represents the susceptance and conductance of the line between node i and node j ; G_{ij} represents the conductance of the line between node i and node j ; $V_{i,s}^t$ the magnitude of the voltage at i^{th} node; $\delta_{ij,s}^t$ is the voltage angles variance at i^{th} and j^{th} nodes; $P_{d,i}^t$ and $P_{CS,j,s}^t$ are the load demand and charging station power, respectively; n_b represents the number of nodes; $Q_{d,i}^t$ is the reactive power demand. $P_{cs,i,s}^{max,t}$ and $P_{cs,i,s}^{min,t}$ are the highest and lowest power of the EV's station at i^{th} node, respectively; n_i^{min} and n_i^{max} are the minimum and maximum allowed number of WT units at i^{th} node, respectively; $Q_{inv,i,s}^t$ represents the reactive power of the interfacing inverter at i^{th} node; $Q_{inv,i,s}^{max}$ and $Q_{inv,i,s}^{min}$ represent, respectively, the highest and lowest reactive power of the interfacing inverter at i^{th} node; V^{min} and V^{max} are the lowest and highest voltage boundaries, respectively; ϕ_b represents a set of the nodes of the system. $\text{SOC}_{n,d,s}$ represents the state of charge (SOC) of n^{th} battery at departure time; $\text{SOC}_{n,min,s}$ represents the minimum SOC determined by the corresponding vehicle owner. Equation (5) represents the upper and lower boundaries of the voltage at the various buses of the distribution system. The proposed planning model of WTS will optimally coordinate between OLTC operations and WTS reactive power support to keep the voltage within the acceptable boundaries, besides other constraints. In this work, the WTSs and the EV charging stations are assumed to be owned by the utility. To generalize the proposed method with respect to different ownerships for WTSs and EV charging stations, proper incentive mechanisms still need to be elaborated, but it is not a target in this work.

3.2. Modeling of EV Battery

When the EVs are connected to the distribution system, their SOC values are variable and depend on the

status of the EV battery once it is charging/discharging. The SOC can be updated each time instant as follows:

$$SOC_{n,s}^t = SOC_{n,s}^{t-1} + \eta_{ch,n} P_{ch,n,s}^t \Delta t \alpha - \frac{\Delta t \beta P_{dc,n,s}^t}{\eta_{dc,n}} \quad (12)$$

where α and $\beta \in \{0,1\}$, and $\alpha, \beta = 0$, since the simultaneous charge and discharge of the EV batteries is not allowed; $P_{ch,n,s}^t$ represents the charging power of n^{th} EV; $P_{dc,n,s}^t$ represents the discharging power of n^{th} EV; $\eta_{ch,n}$ and $\eta_{dc,n}$ are the efficiencies of charging and discharging for n^{th} EV, respectively; $SOC_{n,s}^t$ and $SOC_{n,s}^{t-1}$ are the current and previous SOC of n^{th} EV, respectively. The charging and discharging powers of an EV is a percentage of the full power of the EV's station. The amount of charging and discharging powers depend on many factors as described in the following equations:

$$P_{ch,n,s}^t = \frac{(C_{batt,n} - SOC_{n,s}^t \times C_{batt,n}) \times P_{CS,s}^t}{T_{rem,n} \times \sum_{j=1}^m \frac{1}{T_{rem,j}} (C_{batt,j} - SOC_{j,s}^t \times C_{batt,j})} \quad (13)$$

$$P_{dc,n,s}^t = \frac{T_{rem,n} (SOC_{n,s}^t \times C_{batt,n}) \times P_{CS,s}^t}{\sum_{j=1}^m T_{rem,j} (SOC_{j,s}^t \times C_{batt,j})} \quad (14)$$

in which

$$T_{rem,n} = T_{d,n} - T_{arr,n} \quad (15)$$

where $C_{batt,n}$ is the battery capacity; $T_{arr,n}$ is the arrival time of n^{th} EV; $T_{d,n}$ is the departure time of n^{th} EV. Hence, the total power of the station is distributed among the EVs by the aggregator based on (13)-(15).

3.3. Stochastic nature of EV

The EVs have many stochastic variables such as 1) the arrival time, 2) traveling mileage during the day, 3) parting time, and 4) driving traditions. These variables should be considered in the optimization model. The arrival time of the EVs is a random variable and can be described as a normal pdf [26]. Therefore, the daily arrival time of an EV can be characterized by the following pdf:

$$f_n^t(T_{arr}) = \left(\frac{\exp \left[\frac{-(T_{arr} - \mu_{T_{arr}}^t)^2}{2(\sigma_{T_{arr}}^t)^2} \right]}{(\sigma_{T_{arr}}^t \sqrt{2\pi})} \right) \quad (16)$$

where $\sigma_{T_{arr}}^t$ and $\mu_{T_{arr}}^t$ represent, respectively, the standard deviation and mean of daily arrival time, and their values are, respectively, 5 and 18 hours.

The initial SOC of the EV is affected by many factors such as 1) daily traveling mileage (d_{mn}), 2) all-electric range (AER_n), and 3) battery SOC at the last departure time (e.g., 100%). For protection against degradation of the EV batteries, the depth of discharge should be less than 80%. Hence, the initial SOC of an EV can be mathematically given as follows:

$$SOC_{initial,n}(\%) = \begin{cases} (1 - \frac{d_{mn}}{AER_n}) \times 100, & 0 < d_{mn} < 0.8AER_n \\ 20\%, & d_{mn} > 0.8AER_n \end{cases} \quad (17)$$

$$AER = \frac{C_{batt,n}}{E_{cons/mile,n}} \quad (18)$$

where $E_{cons/mile,n}$ is the consumption energy per mile.

Lognormal pdf is used to represent the daily unpredictability mileage of the EV. The probability manifestation of negative distances is zero, while, for positive distance, a tail extending to infinity [26]. The daily mileage pdf of EV is given as follows:

$$f_n^t(dm) = \frac{1}{dm_n \sqrt{2\pi(\sigma_{dm,n}^t)^2}} \times \exp \left[\frac{-(\ln dm_n - \mu_{dm,n}^t)^2}{2(\sigma_{dm,n}^t)^2} \right], dm_n > 0 \quad (19)$$

where the daily mileage mean (μ_{dm}^t) and the daily mileage standard deviation (σ_{dm}^t) are 22.3 and 12.3 miles, respectively.

4. Modeling of load and wind speed

This section explains the uncertainties of wind speed and load demand. In this work, the hourly wind speed and load demand are modeled using appropriate pdfs. Then, for each hour, the continuous pdf is separated into discrete form, with a step of 1 m/s for wind speed states and 0.1 pu for load demand states. From the WT performance curve, the output power of the WTS can be computed.

4.1. Modeling of hourly wind speed and power output

The hourly wind speed is commonly modeled by using Weibull pdf and can be given, for each hour (t), as follows [20, 27]:

$$f_W^t(v) = \frac{k}{c} \left(\frac{v}{c} \right)^{k-1} \exp \left[- \left(\frac{v}{c} \right)^k \right] \quad (20)$$

where c and k represent, respectively, the scale and shape parameters. Various methods can be utilized to determine these parameters, as given in [28, 29]. In this paper, the parameters of Weibull pdf are determined using the standard deviation (σ_v) and the mean (μ_v) of the wind speed as follows:

$$k = \left(\frac{\sigma_v}{\mu_v} \right)^{-1.086} \quad (21)$$

$$c = \frac{\mu_v}{\Gamma(1+(1/k))} \quad (22)$$

The wind speed probability of a state (w) can be calculated by:

$$P_v^t(G_w) = \int_{v_{w1}}^{v_{w2}} f_W^t(v) \cdot dv \quad (23)$$

where $P_v^t(G_w)$, v_{w1} and v_{w2} represent, respectively, the wind speed probability of state w , the wind speed lower limit of state w , and wind speed upper limit of state w .

For each state, the generated power by each WT unit of the WTS can be computed using WT performance curve and the average wind speed value at this state as follows:

$$P_{WT_w}^t = \begin{cases} 0, & 0 \leq v_{avw} < v_{ci} \\ P_{rated} \times \frac{(v_{avw} - v_{ci})}{(v_r - v_{ci})}, & v_{ci} \leq v_{avw} < v_r \\ P_{rated}, & v_r \leq v_{avw} < v_{co} \\ 0, & v_{avw} \geq v_{co} \end{cases} \quad (24)$$

where v_{ci} is the cut-in speed of the WT; v_{co} is the cut-off speed of the WT; v_r is the rated speed of the WT; v_{avw} represents the wind speed average for state w ; P_{rated} represents the rated

power of the WT; $P_{WT_w}^t$ is the power output of WT unit during time segment t of state w . Note that we have used the same wind data for different WTS locations in the test system. Since the possible WTS locations in the distribution system lie in the same geographic area, wind speed profiles at these various locations have close trends. Therefore, the adopted assumption of utilizing the same wind data for different WTS locations can be accurate in distribution systems.

4.2. Modeling of hourly load demand

Normal pdf is commonly used to model the uncertainty of the demand load [20, 30]. Standard deviation (σ_l) and mean (μ_l) at time segment t are used to represent the pdf of the load demand. Hence, the Normal pdf of the load demand can be mathematically given as follows:

$$f_l^t(l) = \frac{\exp\left[-\frac{(l-\mu_l^t)^2}{2(\sigma_l^t)^2}\right]}{(\sigma_l^t\sqrt{2\pi})} \quad (25)$$

For each state u , the load demand probability of time segment t can be computed as follows:

$$P_l^t(G_u) = \int_{l_{u1}}^{l_{u2}} f_l^t(v) \cdot dv \quad (26)$$

where $P_l^t(G_u)$, l_{u1} and l_{u2} are, respectively, the load demand probability of state u , the lower limit of the load demand of state u , and upper limit of state u .

4.3. A combined model of wind speed and load demand

The amalgamated probability model of the wind speed and demand load can be determined as follows:

$$P_{comb}^t(\lambda_s) = P_v^t(G_w) \times prob_l^t(G_u) \quad (27)$$

The combined model of wind speed and load demand is computed by utilizing all possible amalgamations of wind speed and load demand. Therefore, the whole combined model of the wind speed probability and load demand probability (ψ) can be computed as follows:

$$\psi = [\{\lambda_s, P_{comb}(\lambda_s)\} : s = 1:n_s] \quad (28)$$

in which $P_{comb}^t(\lambda_s)$ contains the elements of the combined wind speed-load demand model based on the matrix λ . The application of the wind speed-load demand model provides comprehensive modeling for enhancing the hosting capacity of WTSs in distribution systems. Note that the wind speed and load demand are considered to be independent in this work.

5. GSA

GSA was developed by E. Rashedi and et al. in [31]. This algorithm is a population-based search one. The performances of GSA are measured based on its mass, which is in ratio to its fitness values. The objects are attracted to each other by the gravity force in which the possible solutions are called agents. These agents are considered as objects. The movements of all agents are directed towards the heavier agents. The optimal solution is described by the agent with the heaviest mass. The mass position (x_i of agent i) is equaled

by a problem solution and a fitness function is utilized to specify its inertial and gravitational masses.

In the beginning, the objects are placed in search space randomly. For each object, the mass value is determined according to its fitness value as follows:

$$M_i = \frac{fit_i(t) - worst(t)}{\sum_{j=1}^N fit_j(t) - worst(t)} \quad (29)$$

where $fit_i(t)$ represents the fitness value of i^{th} object at time t ; $worst(t)$ represents the worst fitness value of the objects at time t ; N represents the number of objects.

To determine the agent acceleration, the total forces from a set of heavier masses that apply on it should be considered based on gravity law which is followed by calculation of agent acceleration using the law of motion as follows:

$$a_i^d(t) = \sum_{j \neq i} r_j \cdot G(t) \frac{M_j(t)}{R_{ij}(t) + \varepsilon} \cdot (x_j^d(t) - x_i^d(t)) \quad (30)$$

Then, the following velocity of the agent can be computed as a portion of its current velocity plus its acceleration as follows:

$$v_i^d(t+1) = r_i \cdot v_i^d(t) + a_i^d(t) \quad (31)$$

Hence, the following position of the agent can be determined as follows:

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1) \quad (32)$$

where $G(t)$ represents the gravity constant; ε represents a very small value; r_i and r_j represent two random numbers in the range $[0,1]$; $R_{ij}(t)$ represents the Euclidian distance between object i and object j ; $v_i^d(t)$ and $x_i^d(t)$ represent, respectively, the velocity and position of the object at time instant t in the dimension d .

The gravity constant $G(t)$, given in (30), can be computed as follows:

$$G(t) = G_0(t)e^{(-\alpha t/itermax)} \quad (33)$$

where $G_0(t)$ represents the initial value; α represents a user-specified constant term; $itermax$ represents the maximum iterations.

6. Proposed method

The solution procedure for enhancing the hosting capacity of intermittent WTSs by using the proposed approach is described in Fig. 2. The solution process comprises three steps. These steps can be described as follows:

Step I: in this step, the whole data of the test system (e.g., line data, bus data, OLTC), historical datasets of load demand, historical datasets of wind speed are read. Based on the historical datasets of load demand and wind speed, the probabilistic model of the wind speed and load demand can be generated in this step. Moreover, this step reads the locations WTSs and charging stations of EVs; besides, it reads their operational constraints and control schemes.

Step II: this step executes the proposed approach in which the developed optimization algorithm is called to enhance the hosting capacity of WTSs based on the outer and inner layers. The optimal charging/discharging power of EVs, reactive power of the interfacing inverters, and OLTC position are determined by the inner layer while the outer

Fig. 2. Solution procedure of the proposed approach

layer maximizes the hosting capacity of the WTSs. In other words, the outer layer suggests candidate solutions (i.e., WTS capacities) and passes them to the inner layer. The inner layer, in turn, computes the optimal charging/discharging power of the EVs, optimal reactive power injected/absorbed by the interfacing inverters, and the optimal position of the OLTC. The charging and discharging power of EV stations are optimally calculated within their constraints expressed by (6). In turn, the amount of the charging and discharging power of each individual EV is computed by (13)-(15). It worth noting that a load flow algorithm is applied to determine the objectives for each state. This consecutive process is recurrent until attaining the convergence conditions of the proposed approach, and the results for each state are saved. Base on the saved results of the different states, the objective function of the outer layer can be computed.

Step III: This is the last phase of the solution process. In this step, all the calculated results (e.g., hosting capacity of WTSs, charging and discharging of EVs, reactive power of the interfacing inverters, and OLTC tap position) are shown.

In this work, we have assumed distributed charging stations through the test system to consider the future directions of increasing EVs. Under such a future scenario, the number of EV charging stations will be considerably increased to multiple charging stations in each geographic area to satisfy the charging requirements of EVs. Regarding the number of WTS sites, we have considered 3 possible locations, but we can reset this number based on the utility and the test system. To apply the proposed method on a practical distribution system, the proposed method is flexible and general to represent the existing EV charging stations and

Fig. 3. One-line diagram of the IEEE 69-bus system

Fig. 4. Number of EVs at each time segment for 60 EVs

Fig. 5. Probability distribution function of initial SOC of the EV batteries

feasible WTS sites according to environmental and social considerations.

7. Results and discussions

7.1 Test system

The IEEE 69-bus distribution test system is chosen to demonstrate the efficacy of the proposed approach for enhancing the hosting capacity of intermittent WTSs. The single-line diagram of the considered system is given in Fig. 3. This system contains only one source with 12.66 kV. Furthermore, it comprises of 69 buses, 68 branches, and 7 laterals. The base active and reactive load demand of the considered system are 3.802 MW and 2.695 Mvar, respectively. The line and load data of the respected test system are obtained from [32]. Multiple WTSs (i.e., three WTSs) are supposed to be connected to the system. These WTSs are placed at buses 11, 18, and 61, and WTS₁, WTS₂, and WTS₃ denote them, respectively. In this paper, WT units with a rated of 200 kW are used [33]; The cut-in speed, rated speed, and cut-off speed of these units are 2.5 m/s, 11.5 m/s, and 20, respectively.

The test system accommodates four charging stations at nodes 33, 36, 52, and 65, and they are symbolized by STA₁, STA₂, STA₃, and STA₄, respectively. Note that each EV charging station is located in a different lateral of the test system. Each station from these charging stations accommodates 60 EVs during the day. In this work, we consider only the cars that involve batteries (i.e. EVs). The distribution of the EVs and the initial SOC for each EV over the day can be determined using (16)–(19) as given in in Figs. 4 and 5, respectively. Tesla Model S battery with a capacity of 85 kWh is utilized with EVs, which are used in this paper. Usually, the owners of EVs arrive home after the workday around 6:00 pm and they are parting to work around 6:00 am. Therefore, the parking period of the EV since arriving till parting is used to be 12 hours. The required SOC of the EV battery at the parting time can be decided by the and it is incorporated in the optimization problem to be met. The maximum charging/discharging power of the batteries is considered to be $0.2C_{batt,n}$ [34]. Historical data sets of three-years for load demand and wind speed are utilized to calculate their pdfs. In this work, the three years are represented by a day throughout these years where this day is subdivided into 24-h time segments. If we consider a year to have 365 days, each time segment then has 1095 (3 years x 365 days per year) load and wind speed level data points. Based on these data, the mean and standard deviation for each time segment can be computed, and so the normal and Weibull probability density functions are constructed for each time segment. Note that the load growth and customer's behavior through the three years are represented by the time-series dataset of the three-years. Therefore, the generated pdf model of load can represent such load growth and customer's behavior which are captured from the original dataset. However, another way to consider the load growth is by utilizing the following formula: $S_i = S_{base}(1 + r)^m$ [35]. Where S_i , S_{base} , r , and m represent the set of the load during year i , the set of the load for the base year, the annual growth rate, and year number, respectively. The simulation results have been carried out in MATLAB environment.

7.2 Case studies

To study and evaluated the performance of the proposed approach for enhancing the hosting capacity of the intermittent WTSS, five different cases have been performed and compared considering the OLTC and the reactive power capabilities of the interfacing inverters. The five cases can be described as follows:

- *Case 0*: this is the base case where we have not considered any of OLTC, reactive power capabilities of the interfacing inverters, or EVs.
- *Case 1*: this case considers only the uncontrolled EV charging.
- *Case 2*: in this case, the reactive power capabilities of the interfacing inverters are considered as VAR sources.
- *Case 3*: only the operation of the OLTC is considered as a control variable in this case.
- *Case 4*: this case considers the OLTC, reactive power capabilities of the interfacing inverters, and optimized EV charging/discharging to enhance the hosting capacity of WTS.

Fig. 6. Voltages profiles at PCC for (a) Case 0, (b) Case 1

Fig. 7. Voltages profiles at PCC for (a) Case 2 (b) Case 3, (c) Case 4

In Case 0 and Case 1, the interfacing inverters work at unity power factor while in Case 2, the interfacing inverters

(a)

(b)

Fig. 8. Optimal movements of the OLTC (a) Case 3, (b) Case 4

(a)

(b)

Fig. 9. Optimal injected/absorbed reactive power of the interfacing inverters (a) Case 2, (b) Case 4

of the WT have capabilities to inject or absorb reactive power based on the amount of generated active power. On the other hand, the operation of the OLTC is considered in Cases 3 and 4. Furthermore, the effect of EVs for enhancing the hosting capacity of WTS with uncontrolled charging scheme (the EVs are charging with a fixed rate of $0.2C_{batt,n}$ regardless of the system state) is considered in Case 1, while the EVs are considered in Case 4 with optimized charging/discharging scheme in which the EVs have the possibility to discharge to the grid through vehicle-to-grid technology (V2G) and the rate of charging/discharging depends on the system state.

(a)

(b)

Fig. 10. Power factor curves of the interfacing inverters associated with the reactive power curves (a) Case 2, (b) Case 4

Fig. 11. SOC of the EVs connected to distribution system through STA₁ for Case 1

7.3 Performance of the proposed approach

In this subsection, the performance of the proposed approach with performing the different cases. Figs. 6 and 7 show the voltage profiles at PCC for the five different cases. In these figures, the voltages at PCC for different states have been plotted as dots for the first location, circles for the second location, and crosses for the third location. On the other hand, the expected voltages (mean voltages) for these states have been plotted as solid lines. By applying the different cases (Case 0- Case 4), the voltages are kept within limits in the case of all states for different buses. It is worth mentioning that the voltage profiles in the case of Cases 2-4 are significantly improved compared to voltage profiles in the case of Cases 0 and 1. These improvements because of employing reactive power capability of the interfacing inverters in Case 2, OLTC in Case 3, and all of OLTC, the reactive power capability of the interfacing inverters, and optimized charging scheme of EVs in Case 4.

Fig. 8 illustrates the optimal actions of the OLTC in Cases 3 and 4. In this figure, the OLTC positions in the case

Fig. 12. SOC of the EVs at charging stations (a) STA_1 , (b) STA_2 , (c) STA_3 , (d) STA_4

Table 1 Comprehensive comparison between different approaches

Case study	WTS location	WTS size (units)	HC (%)	No. of taps movements	V^{min} (pu)	V^{max} (pu)	Avg Q (Mvar)
Case 0	WTS ₁	9	38	-	1.01	1.02	-
	WTS ₂	22	94		0.99	1.01	-
	WTS ₃	1	4		0.96	0.99	-
Case 1	WTS ₁	11	47	-	1.00	1.01	-
	WTS ₂	20	85		1.00	1.01	-
	WTS ₃	2	8		0.97	0.99	-
Case 2	WTS ₁	12	51	-	1.00	1.03	-577.71
	WTS ₂	29	124		0.99	1.02	-13.74
	WTS ₃	1	4		0.97	1.00	313.89
Case 3	WTS ₁	19	82	12	1.01	1.04	-
	WTS ₂	50	215		1.01	1.04	-
	WTS ₃	4	17		0.98	1.02	-
Case 4	WTS ₁	30	129	16	0.98	1.03	-637.43
	WTS ₂	50	215		1.00	1.04	9.03
	WTS ₃	9	38		0.98	1.04	16.64

of Case 3 are higher than those in the case of Case 4 to maintain the voltages within limits. This because of considering the reactive power capability and EVs for voltage regulation along with OLTC in Case 4. The optimal reactive powers which injected/absorbed by the interfacing inverters in Case 2 and Case 4 are demonstrated in Fig. 9. In this figure, the negative amount means the reactive power is absorbed from the distribution system by the interfacing inverters while the positive amount means the reactive power is injected by the interfacing inverters to the distribution system. These injected/absorbed reactive powers have significant effects on voltage regulation and increasing the hosting capacity of WTS.

Fig. 10 shows the power factor (PF) curves of WTSs associated with the reactive power curves. As shown, the calculated power factor of each WTS varies during the day, where it is leading or lagging when the corresponding generated reactive power is injected or absorbed at PCC, respectively. In this work, the whole spare capacity of the interfacing WTS inverters can be used for reactive power

support. Therefore, the range of the power factor varies between 0 and 1. However, if there are boundaries for the power factor, they can be adopted in the proposed method. Under this situation, the reactive power support coming from the interfacing inverters is expected to be reduced, thereby alerting the hosting capacity of WTSs.

The charging/discharging behavior of EV is shown by the SOC of the EV batteries during the parking period. In the case of Case 1, the SOC of the four different charging stations has the same behavior as they are charging with the same fixed charging rate ($0.2C_{batt,n}$). Hence, to avoid results repetition, only the SOC of the EVs at STA_1 is shown in Fig. 11. This figure shows that all EVs are fully charged at their departure time, which satisfies the owner's requirements for daily driving. In this case (Case 1), EVs are charging with the fixed rate until their SOC reaches 100%. On the other hand, in the case of Case 4, the EVs can charge/discharge from/to the distribution grid through V2G technology (i.e., the SOC are increasing and decreasing) in which the charging/discharging rate depends on the system state. The

Fig. 13. Total sizes of WTS and total hosting capacities and by applying different cases.

SOC of the EVs at STA₁, STA₂, STA₃, and STA₄ are given in Fig. 12. This figure shows that the EVs can charge/discharge from/to the distribution system while the SOC of all EVs at departure time is high enough for daily driving (more than 90%).

7.4 Comprehensive comparison with exciting approaches

In this subsection, we have compared the proposed approach (Case 4) with three existing approaches, which are called Case 1, Case 2, and Case 3. Specifically, a comprehensive comparison of the different case studies in terms of size of WTS (number of WT units at each location), hosting capacity, number of tap movements, maximum mean voltage (V^{max}), minimum mean voltage (V^{min}), and average reactive power (Avg. Q) of the interfacing inverters as given in Table 1. From this table, it can be observed that the minimum and maximum mean voltages are kept within limits. On the other hand, the hosting capacity of WTS is variable and depends on the location of the WTS and the executed case. For instance, the hosting capacity of WTS at bus 11 (WTS₁) is 9%, 11%, 12%, 19%, and 30% in the case of Case 0, Case 1, Case 2, Case 3, and Case 4, respectively. It is also observed that enabling the reactive power capability of the interfacing inverter and considering EVs with an optimized charging scheme (Case 4) give a high hosting capacity of WTS. Furthermore, the optimal movements number of OLTC and reactive power injection/absorption by the interfacing inverters depend on the applied case. The numbers of tap movements in the case of Case 3 and Case 4 are 12 and 16, respectively. The total optimal size of the WTS (MW) and the total hosting capacity are compared in Fig. 13. From this figure, the minimum and maximum size of WTS are 6.37 MW and 17.85 MW with a hosting capacity of 136% and 382% by applying Case 0 and Case 4, respectively. The proposed approach (Case 4) shows the best results for enhancing the hosting capacity of WTS compared to the other existing approaches (Cases 1-3). Therefore, it is highly recommended for enhancing the hosting capacity of WTS in distribution systems.

8. Conclusions

The integration of high penetrations of WTSs can deviate the operation of distribution systems from the standard operational condition. In this paper, we have proposed an optimization model for enhancing the hosting capacity of WTSs, considering their intermittent generations

in distribution systems. Various control variables are optimized simultaneously, and so the hosting capacity of WTSs has been significantly improved in distribution systems. These control variables are the operation of OLTC taps, charging schemes of EV batteries, and reactive power of multiple WTSs. A bi-level optimization algorithm with inner and outer layers has been developed to solve this planning model of WTSs. Simulation results have been performed on the 69-bus distribution test feeder with 4 stations of EVs. The results with different cases reveal the effectiveness of the proposed method, thanks to the simultaneous optimization of the control devices. In the future, the proposed method will be tested on other test systems with different configurations and sizes.

9. References

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