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Impact of wind uncertainty, plug-in-electric vehicles and demand response program on transmission network expansion planning

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ABSTRACT

The aim of this paper is to minimize the total cost of the system by incorporating wind power and plug-in-electric vehicles (PEVs) along with demand response (DR) program. The methodologies have proposed in contrast with the conventional algorithm in which the transmission line investment cost has been minimized without considering the dynamism of the deregulated environment. Moreover, the transmission network planning enhances the competitiveness of the power market, where more market players can participate. In this situation, the network planner has an important role in assessing the needs for transmission investments. Now-a-days practice of the network planner is to utilize more renewable power resources, PEVs and implementation of different electricity price tariffs. To achieve more benefits of PEVs and wind energy, their optimal utilization is a major concern. This paper proposes a mathematical model for solving the combined effect of PEVs and wind power integration with incentive-based DR program on static transmission network expansion planning (STNEP) problem. To solve this non-linear and non-convex problem, a nature-inspired optimization algorithm named gbest-guided artificial bee colony algorithm (GABC) is applied due to its robustness. The algorithm's performance is evaluated through modified IEEE 24-bus, Brazilian 46-bus and Colombian 93-bus system. The test results indicate that the combined effect of DR, PEVs and wind has reduced the total system cost significantly.

Introduction

Economic benefits and environmental issues are the two major concerns of the power system planning and its operations. Several strategies such as integration of renewable energy resources are adopted by the network planner to overcome these problems [1,2]. As there are limitations of conventional energy resources, major attraction is moving towards the renewable power resources and other portable power devices. The power system planning is to be done in an optimized way to prevent the system failure, load shedding and reliability. However, the transmission expansion planning (TEP) has an important role to play, as it helps to find out the new transmission facilities required. TEP determines "what," "where", and "when" new transmission facilities to be installed to the system requirements. Transmission network expansion planning (TNEP) is categorized as static or dynamic TNEP problems. The static TNEP problem is a single period planning, whereas the dynamic TNEP is a multi-period planning [3].

Since 1970's TNEP problem has been solved as an optimization problem [4]. Thereafter many researchers have worked to solve the TEP problem by applying various techniques and the research done so far on TEP problem has been reported in [1,2]. Starting from the classical optimization methods [4–6], heuristic methods [7–9] and population/or nature inspired algorithms [10–18] have been applied to solve TEP problem.

Generally big vulnerability comes in finding "optimal solution" by mathematical optimization methods due to the internal limitations of the optimization techniques itself, such as the presence of non-linearity and stochastic modeling. Furthermore, this leads to large computational burden to the TEP planner. Therefore, these days heuristic and meta-heuristic techniques are used to solve TEP problems, which provide fast convergence and rapid calculation.

In the literature various issues and difficulties related to TEP problems have been reported in [13,15–17]. In [13], the multiyear TEP problem has been solved by considering demand uncertainty nature to find out the most suitable group of projects, as well as their scheduling along with the planning horizon. In [15], the TEP problem has been solved by considering security issue and the changes in the network configuration and affects in the investment cost during any line outage has been presented. The multi-stage

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Nomenclature

A_i^j incentive price paid to the consumer in jth load period (US $/MW)
$B\left(d_i^j\right)$ customer's income in the jth load period (US)
$a_i,\ b_i,\ c_i,\ d_i,\ e_i$ cost coefficient of the ith generator
c scale factor (units of wind speed)
C_{DRj} cost of demand response for jth load period (US $)
$C_{Lik}(\cdot)$ cost function of new line added to the $i-k$ right-of-ways (US $)
$C_i(\cdot)$ total fuel cost function of the ith generator (US $/h)
$C_{PEVi}(\cdot)$ cost function of total number of vehicle connected to bus i (US $)
$C_{wdi}(\cdot)$ direct cost function of ith wind farm (US $/h)
$C_{pwi}(\cdot)$ and $C_{rwi}(\cdot)$ underestimation and overestimation cost functions of the ith wind farm (US $/h)
d_{wi} direct cost coefficient for the ith wind farm (US $/MW h)
$d_{o_i}^j$ and d_i^j new load demand and initial load demand at bus i for jth load level (MW)
CDR cost of demand response participation (US $)
TWC total wind power utilization cost (US S/h)
E_i^j elasticity of jth load level with respect to ith bus
ECV energy cost of the PEV
F fitness function
FC fuel cost (US $/h)
f_{ik}^j active power flow in the $i-k$ branch for jth load level (MW)
$f_V(v)$ and $F_V(v)$ weibull probability and cumulative distribution function (CDF) density function
f_{ik}^{max} active power flow limit on the $i-k$ branch (MW)
$f_W(P_w)$ WECS wind power pdf
TLC transmission line investment cost (US $)
k shape factor
k_{pi} and k_{ri} underestimation and overestimation cost coefficient for the ith wind farm (US $/MW h)
L_d number of load levels
n_{ik}^o and n_{ik}^j initial number of lines and new lines added jth load level to the $i-k$ branch
n_{ik}^{max} maximum number of lines that can be added to the $i-k$ branch
N_{lk} set of lines connected to bus k
N_{PEV}^{max} maximum number of PEVs
$N_v,\ N_g$ and N_w number of PEVs, thermal generators and wind farms
pen_i^j penalty at bus i for jth load level (US $/MW)
P_{gi}^j active power generation at the ith bus at load level j (MW)
$P_{inc}\left(\Delta d_i^j\right)$ total payment for incentive (US $)
$PEN\left(\Delta d_i^j\right)$ total payment for penalty (US $)
P_{gi}^{min} and P_{gi}^{max} active power generation lower and upper limit at the ith bus (MW)
P_{dk}^j active load at bus k for load level j (MW)
P_{PEVi}^j power generated by the vehicle connected to bus i at load level j (MW)
P_{wi}^j scheduled wind power from the ith wind farm at load level j (MW)
$P_{wi,av}^j$ available wind power from the ith wind farm at load level j (MW)
P_{wr} and P_w rated wind power and output power of the ith wind farm (MW)
$Prob\{\cdot\}$ probability of events
TC total cost (US $)
$v,\ v_{ci},\ v_{co}$ and v_r wind speed, cut-in, cut-out and rated wind speed m/s
γ_{ik} susceptance of a branch between buses $i-k$
θ_m^j and θ_n^j phase angle at buses m and n for load level j (rad)
$\rho_{o_i}^j$ and ρ_i^j original electricity and spot electricity prices at bus i for jth load (US $/MW h) level (US $/MW h)
Ω set of all candidate lines

TEP problem in a deregulated electricity market has been presented. The objective is to minimize the investment and operating costs with the inclusion of $N-1$ reliability criterion [16]. In [17], the impact of distributed generation (DG) on sub-transmission system expansion planning has been presented, which gives the details about the optimal location and capacity of the substation and DGs.

The wind related issues on TEP problem has been reported in [19–23]. In [19], the reliability issue considering large wind farm and load uncertainty has been described. The analyses described the maximum wind energy capacity that is penetrated to a specified place. The impacts of large-scale wind integration have been solved by taking investment, risk and congestion costs, reserve market and reserve availability costs, and wind power investment cost in [20–23]. The security and reliability constraints have been considered to minimize the system cost. However, none of the mentioned references includes the wind power utilization cost, underestimation cost, overestimation cost and the optimal placement of wind turbine on TNEP problem so far.

In a competitive electricity market, new incentive policy influences the consumers to take more participation in DR programs. DR can be defined as the changes in electricity consumption patterns by the end-user customers, according to the changes in the price of electricity over a period of time from their normal usage patterns [24]. Implementation of DR program is found as an alternative to generation and transmission expansion [25]. Demand response (DR) programs have been widely studied in unit commitment (UC) problem some of the papers are in [26–29]. In [26,27], two types of DR programs have been reported, and their impacts on load shape, load level, and benefits to the customer have been analyzed. DR scheduling by a stochastic model for security-constrained UC in the wholesale electricity market has been solved, and the benefits of demand-side reserve in electricity markets has been presented in [28,29]. From the literature reviewed, it has been found that only few researchers have reported the implementation of DR programs for TEP problem [30,31]. In [30], TEP problem has been solved by incorporation of demand response schedule considering wind power penetration. In [31], a price-based DR program has been implemented on the TEP problem. However, in both the papers the objective is to minimize the total cost of the system, but the detail related to the minimized value of cost, transmission line configuration and the impact on load demand have not been adopted.

According to the electric power research institute (EPRI), it is expected that by 2020 up to 35% of the total vehicles in the U.S. will be PEVs [32]. The PEVs either in the form of source as a vehicle to grid (V2G) technology or load as a grid to vehicle (G2V) technology studies in the different fields of the power systems have been reported in the literature recently [33–42]. The proper scheduling of PEVs prevents overloading of the network, which leads to the congestion free operation. The researches have studied the applications of PEVs on the distribution network [33–35], UC problem [36], economic load dispatch problem [37–39] and transmission network [40–42].

In [33], the detailed review about the present condition, implementation, benefits, and impact of V2G/G2V technologies on distribution system has been presented. In [34], coordination of PEVs and photovoltaic generation systems to minimize the overall cost of the system has been reported. The impact of capacity variation of PEV on distribution network investment and losses has been presented in [35]. In [36], the UC problem has been solved by incorporating V2G to minimize the cost and emission of the system. The coordination of the charging/discharging behaviors of PEVs to minimize the operational of the total system has been presented in [37]. To minimize the total generation cost of the entire system by considering the uncertainties of PEVs and wind power, an economic dispatch model has been discussed in [38]. In [39], a probabilistic constrained load flow problem by integrating PEV and wind power generation to minimize the operation of the system has been presented. In [40], the cost-benefit analysis has been investigated through the optimal PEV coordination schemes on the transmission network. The integration of PEVs with wind power penetration on the transmission network in deregulated market and their impact on the energy cost of PEV has been analyzed [41,42]. It has been found from the literature reported that the application of PEVs on the TNEP problem has not been studied.

The gbest-guided artificial bee colony (GABC) optimization algorithm is the modified version of ABC algorithm, which is a population-based search optimization technique [43,44]. It is inspired by the intelligent foraging behavior of honey bees. The algorithm has been utilized for solving power system problems such as economic load dispatch, UC and load flow [45–47]. From the results reported in [45–47] it has been found that the algorithm proves its fast convergence and robustness.

This paper proposes a mathematical structure, which is a combination of PEVs and wind power uncertainty along with consideration of wind power utilization cost, underestimation cost and overestimation cost model with the DR program for solving the DC power flow model based STNEP problem to minimize the total system cost. The GABC algorithm is applied to solve this complex optimization problem because of its versatility and fast convergence. The algorithm is verified on the modified IEEE-24 bus, Brazilian-46 bus and Colombian-93 bus test system. The performance of the GABC algorithm is compared with the results reported by other researchers. The main contributions of this paper are following:

1. To study the effect of wind power uncertainty on STNEP problem.
2. To study the effect of PEVs concept on STNEP problem.
3. To study the combined effect of the DR program and PEVs with wind uncertainty on STNEP problem.

The paper is organized as follows: Section "Basic Artificial Bee Colony (ABC) optimization algorithm" presents the basic ABC algorithm. The overview of GABC algorithm is presented in Section "Gbest Artificial Bee Colony Algorithm (GABC)". In Section "Problem formulation", the proposed problem formulation is described. In Section "Implementation of GABC algorithm to the static TNEP problem" implementation of the GABC algorithm on proposed STNEP problem is described. Illustration of the systems under study and results are presented in Section "The systems under study and results". Discussions and conclusions are given in Sections "Discussion on the results" and "Conclusion" respectively.

Basic Artificial Bee Colony (ABC) optimization algorithm

Artificial Bee Colony (ABC) is one of the popular meta-heuristic algorithms, which is inspired by the collective intelligent behavior of honey bees for hunting for food. The ABC algorithm has been introduced and developed by Basturk B and Karaboga D [48]. It consists of three artificial bees groups, namely employed bees, onlooker bees and scout bees. The position of each food source signifies a probable and possible solution of the defined optimization problem. The nectar amount of the food source represents the quality or fitness of the solution.

Employed bees are the bees that are going to the food source randomly; they carry information and share it with other bees waiting at the hive regarding location and the profitability of that particular food source. The bees are waiting in the dance area for making the decision to choose a food source based upon information given by the employee bees known as onlooker bees and bees which carrying out random search around the swarm to find food source are scout bees. The ABC algorithm follows the same process for optimization and the steps mentioned below are repeated until a termination criterion is reached.

Initialization of the parameters

The algorithm has few input/control parameters such as population size (Ns), the number of food source, number of employed and onlooker bees, the number of trials after which the food source is assumed to be abandoned called as limit, and finally the stopping criterion (maximum number of iterations).

Initialization of the populations

After feeding the input parameters, the ABC algorithm generates arbitrarily distributed initial population P_{pop} of Ns vectors of candidate solutions as (1),

$$P_{pop} = [X_1, \ldots X_i, \ldots, X_{Ns}]^T \tag{1}$$

where $X_i = [x_{i1}, \ldots, x_{ij}, \ldots, x_{iD}]$ represents the ith food source of D-dimensional vector, then each food source is generated as follow:

$$x_{ij} = lower_{boundj} + (upper_{boundj} - lower_{boundj}) * rand,$$
$$\text{for } j = 1 \ldots D \text{ and } i = 1 \ldots Ns \tag{2}$$

Employed bees phase

At this position, each employed bee finds the new food source position v_{ij} by utilizing the old position using (3)

$$v_{ij} = x_{ij} + w_{ij} * (x_{ij} - x_{kj}) \tag{3}$$

where w_{ij} is a random number between [−1,1], and $k \in \{1, 2, \ldots, Ns\}$ and $j \in \{1, 2, \ldots, D\}$ are randomly chosen indexes. After selection of a new position, the nectar amount is compared between new and old position; if the new position is found better than the old position, a new position is retained; otherwise it is discarded. The greedy selection method is used for the choice of the best and the worst.

Onlooker bees phase

The onlooker bees select a food source according to the probability calculated by (4) associated with that food source.

$$P_{probability_i} = \frac{fitness_i}{\sum_{j=1}^{Ns} fitness_j} \tag{4}$$

where $fitness_i$ is the fitness value of ith solution, and Ns is the number of food source. Similar to the employed bees phase, the onlooker bees also modify their position using (3) and repeat the same.

Scout bees phase

If a food source position cannot be enhanced during a specified number of trials (limit) then it is assumed to be abandoned. Assume that the abandoned source is x_{ij} and $j \in \{1, 2, \ldots, D\}$, then the new food source found by the scout bees to be replaced by the abandoned position by using (5),

$$x_{ij} = x_{jmin} + rand[0,1] * (x_{jmax} - x_{jmin}) \tag{5}$$

For each candidate source position v_{ij} is produced and estimated by the artificial bee, its quality is compared with its old position. If the new position is found better than the old position, it replaces the old position and if not the old position is retained in memory. In the complete process, it is considered that at each cycle at maximum only one scout bee goes outside for hunting a new food source.

Gbest Artificial Bee Colony Algorithm (GABC)

In ABC algorithm the solution search equation described as in (3) and the probability of getting a random solution for the best and the worst solution are same. Also, (3) has good exploration, but poor exploitation. In order to achieve good optimization, performance the exploration and exploitation abilities should be equally balanced. Therefore, to achieve this (3) is modified to improve the exploitation as follows [44]

$$v_{ij} = x_{ij} + \emptyset_{ij}(x_{ij} - x_{kj}) + \psi_{ij}(y_j - x_{ij}) \tag{6}$$

where the term added in (3) is gbest term, y_j is the jth element of the global best solution, and ψ_{ij} is an uniform random number in $[0, C]$, where C is a non-negative constant. By adding this term the exploitation ability of ABC algorithm is increased, and the modified ABC algorithm is named as gbest-guided ABC (GABC) algorithm. The value of C plays an important role in improving the exploitation.

Problem formulation

The objective of the TNEP problem is to minimize the total cost under various economic and technical constraints. The assumptions made for the proposed STNEP problem are:

1. A lossless DC power flow is adopted to model the STNEP problem.
2. The STNEP problem is solved for 100% load level period, and it is assumed that the transmission lines expanded are cable to cater the requirements of rest planning horizon.
3. The spot price and the electricity price are assumed to be same.
4. The group PEVs is installed at a particular location, and they are considered as a source during peak load periods and as a load during off-peak periods.
5. The vehicle battery life cost is not included in the cost function of PEVs.

The proposed STNEP model

In this paper, an equivalent objective of maximizing the social welfare is to minimize the sum of the investment cost as transmission line investment cost and the operating cost as a summation of the fuel cost of thermal generating unit, the wind power utilization cost, the cost of demand response participation and the energy cost of the vehicles connected to the grid is considered and it is formulated as follows:

Minimize
Total Cost,

$$F = Investment\ cost + Operating\ cost \tag{7}$$

$$= \sum_{i,k\in\Omega} C_{Lik}(n_{ik}) + \alpha \cdot \left\{ \sum_{j}^{Ld} \cdot \left[\sum_{i}^{N_g} C_i\left(P_{gi}^j\right) + \sum_{i}^{N_w} \left(C_{wdi}\left(P_{wi}^j\right) + C_{pwi}\left(P_{wi,av}^j - P_{wi}^j\right) + C_{rwi}\left(P_{wi}^j - P_{wi,av}^j\right)\right) + \sum_{i}^{N_v} C_{PEVi}\left(P_{PEVi}^j\right)\right] + \sum_{i}^{L_d} C_{DRi} \right\} \tag{8}$$

The model presented by (8) is analyzed by considering different combinations of cost components. The terms in (8) are explained as follows:

The first term $C_{Lik}(n_{ik})$ in the proposed objective function (8) is the traditional STNEP cost model i.e. cost of new transmission line [11–13,17,49–51] and is given as

$$C_{Lik}(n_{ik}) = CL_{ik}n_{ik} \tag{9}$$

The second term $C_i\left(P_{gi}^j\right)$ is the thermal generation cost and it is represented by the quadratic function of operation cost of thermal generation considering the valve-point effect, which is given by [52]:

$$C_i\left(P_{gi}^j\right) = a_i\left(P_{gi}^j\right)^2 + b_iP_{gi}^j + c_i + \left| d_i sin\left\{e_i\left(P_{gi}^{min} - P_{gi}^j\right)\right\}\right| \tag{10}$$

The third term $C_{wdi}\left(P_{wi}^j\right)$ is a direct cost component and which is the linear cost function of wind power. This amount is paid by the system operator when they consume wind output power; if they do not own the wind generators self otherwise it's equal to zero.

$$C_{wdi}\left(P_{wi}^j\right) = d_{wi}P_{wi}^j \tag{11}$$

The fourth term $C_{pwi}\left(P_{wi,av}^j - P_{wi}^j\right)$ gives the underestimation cost (penalty cost) of wind power when the system operators do not utilize all available wind power (i.e. wind power generated is more than the expected power) and it is determined by using the distribution function [45,53]. This cost function is given by (12)

$$C_{pwi}\left(P_{wi,av}^j - P_{wi}^j\right) = k_{pi}\left(P_{wi,av}^j - P_{wi}^j\right) = k_{pi}\int_{P_{wi}^j}^{P_{wri}^j}\left(P_w - P_{wi}^j\right)f_W(P_w)dP_w \tag{12}$$

The fifth term $C_{rwi}\left(P_{wi}^j - P_{wi,av}^j\right)$ represents the overestimation cost (reserve cost) model of wind power, which is similar to the underestimation cost, but in this case the amount paid by the system operator due to wind power generated is less than the expected power and it is found by using the distribution function [45,53], i.e.,

$$C_{rwi}\left(P_{wi}^j - P_{wi,av}^j\right) = k_{ri}\left(P_{wi}^j - P_{wi,av}^j\right) = k_{ri}\int_0^{P_{wi}^j}\left(P_{wi}^j - P_w\right)f_W(P_w)dP_w \tag{13}$$

The sixth term $C_{PEVi}\left(P_{PEVi}^j\right)$ gives the energy cost of the vehicles. The vehicle owners may decide their vehicle charging/discharging period in order to get more benefits depending upon the spot electricity price. The energy cost of the vehicle can be written as [40]

$$C_{PEVi}\left(P_{PEVi}^j\right) = P_{PEVi}^j * \rho_i^j \tag{14}$$

Finally, the last term C_{DRj} represents the cost for jth load level of demand response participation. The execution of various types of demand response program leads to an extra cost for the independent system operator (ISO) [27] and it is calculated by using (15)

$$C_{DRj} = -d_{o_i}^j * \left[\frac{A_i^{2^j} * E_i^j}{\rho_{o_i}^j}\right] \tag{15}$$

where α is the weighting factor which is used to equalize between the investment cost and the operating cost, and its value is selected between 10 and 10,000 after several experimentation.

Equality and Inequality constraints of PEVs and STNEP

The constraints are incorporated in solving process so as to prevent the system from failure. These constraints are organized as follows:

1. *Vehicle balance in STNEP*: As per the registered/forecasted PEVs, the total number of vehicles should be less than or equal to the maximum number of PEVs for the scheduling of the specified period.

$$\sum_{t=1}^{hr} N_{PEV}(t) \leqslant N_{PEV}^{max} \tag{16}$$

2. *Charging–discharging frequency*: In this case multiple charging–discharging facilities of PEVs are considered.
3. *State of charge (SoC)*: It is assumed that each vehicle can store energy up to 90% and discharge up to 20% of its maximum energy.
4. *Efficiency (η)*: Battery efficiency should be taken under consideration.
5. *Power balance*: PEVs are assumed as a source during peak load period and as a load in off-peak load period [33–36]. Along with this, the power supplied by the thermal generators and wind farms must satisfy the load for that period,

$$\sum_{\forall i \in N_{lk}} f_i^j + \sum_{\forall i \in N_{lk}} P_{gi}^j + \sum_{\forall i \in N_{lk}} P_{wi}^j \pm \sum_{\forall i \in N_{lk}} P_{PEVi}^j - P_{dk}^j = 0 \quad k = 1, \ldots, N_b$$
$$\begin{cases} P_{PEV} = P_{PEV}, & \textit{During Discharging period} \\ P_{PEV} = -P_{PEV}, & \textit{During Charging period} \end{cases} \tag{17}$$

6. *Maximum power flow limits*: In order to maintain system stability, and the line loading should be less than its thermal limit.

$$\sum_{\forall i \in N_{lk}} \left| f_i^j \right| \leqslant \left(n_i^o + n_i^j \right) f_i^{max} \tag{18}$$

In the DC power flow model, power flow between branches in (18) is calculated by using (19).

$$f_{ik}^j = \gamma_{ik} \left(n_{ik}^o + n_{ik}^j \right) \left(\theta_m^j - \theta_n^j \right), \; m \neq n, \; \forall m, n \in N_b \tag{19}$$

7. *Power generation limits*: Each power generating source has generation range represented as

$$P_{gi}^{min} \leqslant P_{gi}^j \leqslant P_{gi}^{max} \tag{20}$$

$$0 \leqslant P_{wi}^j \leqslant P_{wri} \tag{21}$$

8. *Line expansion limits*: The expansion of new parallel lines should be within the range specified as

$$0 \leqslant n_{ik}^j \leqslant n_{ik}^{max} \tag{22}$$

Wind speed and turbine generator model

The wind energy is highly sensitive to the wind speed and due to the unpredictable nature of wind, many related models are studied. However, it is seen from the previous literature that [53,54] the Weibull distribution is commonly used to represent the wind speed character. Therefore, in this paper also the Weibull probability density function (PDF) is used. The Weibull probability density function and the cumulative distribution function (CDF) are calculated by (23) and (24) respectively.

$$f_V(v) = \left(\frac{k}{c}\right)\left(\frac{v}{c}\right)^{k-1} exp^{-\left(\frac{v}{c}\right)^{k-1}}, \quad 0 < v < \infty \tag{23}$$

$$F_V(v) = \int_0^v f_V(\tau) d\tau = 1 - exp^{-\left(\frac{v}{c}\right)^k} \tag{24}$$

Once the intermittent nature of the wind is considered as an arbitrary variable, the output power of the wind energy conversion system (WECS) may also be considered as a random variable. The output of the WECS [53] with different wind speeds is stated as:

$$P_w = 0, \quad \textit{for } v < v_{ci} \textit{ and } v > v_{co} \tag{25}$$

$$P_w = P_r \left(\frac{v - v_{ci}}{v_r - v_{ci}} \right), \quad \textit{for } v_{ci} \leqslant v \leqslant v_r \tag{26}$$

$$P_w = P_r, \quad \textit{for } v_r \leqslant v \leqslant v_{co} \tag{27}$$

From the Weibull function, the probability of wind power output at zero, rated and intermediate position between them can be generated from Weibull PDF by using (28)–(30) respectively [53]:

$$\begin{aligned} Prob\{P_w = 0\} &= F_V(v_{ci}) + (1 - F_V(v_{co})) \\ &= 1 - \exp\left(-\left(\frac{v_{ci}}{c}\right)^k\right) + \exp\left(-\left(\frac{v_{co}}{c}\right)^k\right) \end{aligned} \tag{28}$$

$$\begin{aligned} Prob\{P_w = P_r\} &= F_V(v_{co}) - F_V(v_r) \\ &= \exp\left(-\left(\frac{v_r}{c}\right)^k\right) - \exp\left(-\left(\frac{v_{co}}{c}\right)^k\right) \end{aligned} \tag{29}$$

where $\lambda = \frac{P_w}{P_r}$ and $\beta = \left(\frac{v_r - v_{ci}}{v_{ci}}\right)$

$$f_W(P_w) = \frac{k\beta v_{ci}}{c} \left(\frac{(1 + \lambda\beta) v_{ci}}{c} \right)^{k-1} exp\left(-\left(\frac{(1 + \lambda\beta) v_{ci}}{c} \right)^k \right) \tag{30}$$

Demand response modeling

In a vertical electricity market, the consumers are paying electricity price irrespective of their consumption. As in the deregulated market the independent system operator (ISO) is influencing consumers to decrease or shift their loads when the price is more. DR program is divided into two main categories as in [24] (i) Incentive-based programs and (ii) Price-based programs. In this paper incentive-based DR program is implemented and for different load levels different elasticity factors are considered to show their effects on price, demand and the consumers benefit.

Elasticity is defined as the demand sensitivity with respect to the electricity price values [27]. The elasticity of *j*th load level with respect to *i*th bus can be written as:

$$E_i^j = \frac{\partial(d_i^j)}{\partial(\rho_i^j)} = \frac{\rho_{o_i}^j}{d_{o_i}^j} * \frac{\mathrm{d}(d_i^j)}{\mathrm{d}(\rho_i^j)} \tag{31}$$

As the electricity price increases in a particular period, the consumers are intended to shift their loads to another interval or otherwise try to reduce the consumptions. To tackle the price variations, loads reacts [55] in two ways: single period loads and multi-period loads. The single period loads are the loads that are not able to shift to the other intervals, and they could be only connected or disconnected to take part in the price variations. These are sensitive to a single period and known as self-elasticity. The multi-period loads are the loads that can be shifted from peak load period to off-peak or low period. These are sensitive to a multi-period and known as cross-elasticity. In the proposed method, a single period load modeling is considered and the participation of customers in DR programs and the economic load model presented in [26] is applied.

Single period modeling

Based on the incentive $\left(A_i^j\right)$ and penalty $\left(pen_i^j\right)$ values offer, the consumers changes its demand as

$$\Delta d_i^j = d_{o_i}^j - d_i^j \tag{32}$$

So, the total incentive price $P_{inc}\left(\Delta d_i^j\right)$ paid to the consumers for the demand for jth load level at ith bus during the DR program is given as:

$$P_{inc}\left(\Delta d_i^j\right) = A_i^j * \left[d_{o_i}^j - d_i^j\right] \tag{33}$$

If the consumers are participating in DR program and not obeying the rules, the penalty (pen_i^j) will be charged and the total penalty $PEN\left(\Delta d_i^j\right)$ will be calculated as:

$$PEN\left(\Delta d_i^j\right) = pen_i^j * \{d_{o_i}^j - d_i^j\} \tag{34}$$

The consumers benefit CB for jth load level will be:

$$CB = B\left(d_i^j\right) - d_i^j * \rho_i^j + P_{inc}\left(\Delta d_i^j\right) - PEN\left(\Delta d_i^j\right) \tag{35}$$

For maximizing consumers benefit, $\frac{\partial CB}{\partial d_i^j} = 0$

$$\frac{\partial\left(B\left(d_i^j\right)\right)}{\partial\left(d_i^j\right)} = \rho_i^j + A_i^j + pen_i^j \tag{36}$$

And from [22]:

$$\frac{\partial\left(B\left(d_i^j\right)\right)}{\partial\left(d_i^j\right)} = \rho_{o_i}^j * \left\{1 + \frac{d_i^j - d_{o_i}^j}{E_i^j * d_{o_i}^j}\right\} \tag{37}$$

By comparing (36) and (37)

$$\rho_i^j + A_i^j + pen_i^j = \rho_{o_i}^j * \left\{1 + \frac{d_i^j - d_{o_i}^j}{E_i^j * d_{o_i}^j}\right\} \tag{38}$$

Therefore, consumer's consumption will be:

$$d_i^j = d_{o_i}^j * \left\{1 + \frac{E_i^j * [\rho_i^j - \rho_{o_i}^j + A_i^j + pen_i^j]}{\rho_{o_i}^j}\right\} \tag{39}$$

Accordingly, the cost of demand response participation can be calculated as [27]:

$$C_{DRi} = A_i^j * \left(d_{o_i}^j - d_i^j\right) \tag{40}$$

By assuming the electricity price before and after demand response to be equal and the penalty to be zero, (38) and (39) become

$$d_i^j = d_{o_i}^j * \left\{1 + \frac{E_i^j * [A_i^j]}{\rho_{o_i}^j}\right\} \tag{41}$$

$$C_{DRi} = -d_{o_i}^j * \left[\frac{A_i^{2^j} * E_i^j}{\rho_{o_i}^j}\right] \tag{42}$$

The ISO has to pay this amount to the consumers as an incentive when they are participating in DR programs.

Implementation of GABC algorithm to the static TNEP problem

This section provides the details of the application of GABC optimization technique to solve the proposed STNEP problem. The flow chart is illustrated in Fig. 1 and the steps to be followed are:

(1) Read all the network data and the algorithm control parameters.
(2) Create the random initial population vector of possible optimal solution using (1) according to the case study under consideration.
(3) The GABC optimization algorithm iterates over the employed bees, onlooker bees and scout bees phases until the termination criterion is reached.
(4) Run DC load flow for every change in food source position by simultaneously checking for the system constraints using (16)–(22). The penalty factor method is used to handle the system constraints.

As quick as the stopping criteria is achieved, the solution obtained by the GABC algorithm is the one with minimum transmission line investment cost and total cost, which at the same time satisfies all the system constraints.

The systems under study and results

System under study

The static TNEP study is performed in MATLAB environment by applying the GABC optimization algorithm. The test systems used are (1) a modified IEEE 24-bus system (2) Brazilian 46-bus system [10] and (3) Colombian 93-bus system [56]. Original IEEE 24-bus network data has been taken from [48] and the thermal generator cost characteristic of ith unit are modified by using data available in [51]. Details are shown in Tables 1 and 2. It is assumed that the maximum number of three new parallel lines may be installed in each possible path.

For solving the STNEP problem, the value of P_{gi}^{min} is set to 0 MW. For the implementation of the DR program at different load levels, the total duration of 8760 h is considered [41]. The maximum numbers of PEVs considered are 500,000. Spot electricity price (SP) is extracted from [25] and the price elasticity of each load level is taken from [54]. Spot electricity price, price elasticity, incentive price and penalty price offered to the consumers for jth load level at ith bus are same. The details of wind generators and PEVs parameters used are given in Table 3.

To examine the effects of various situations on the proposed STNEP problem, eight different scenarios are demonstrated.

- The scenario-1 is assumed to be the base case in which the STNEP problem is solved only for a given generation and load plan.
- In scenario-2, the power generation of the generating units is allowed to vary between their minimum and maximum generating limits.
- The impact of EDRP-DR program is analyzed in scenario-3.
- Integration of wind power and PEVs at load bus is analyzed in scenario-4 and scenario-5.
- In scenario-6, the DR program is examined with the integration of PEVs at load bus.
- In scenario-7, the wind power and PEVs are integrated at load bus for the analysis.
- The combined impact of the PEVs, wind power uncertainty and DR program is illustrated in scenario-8.

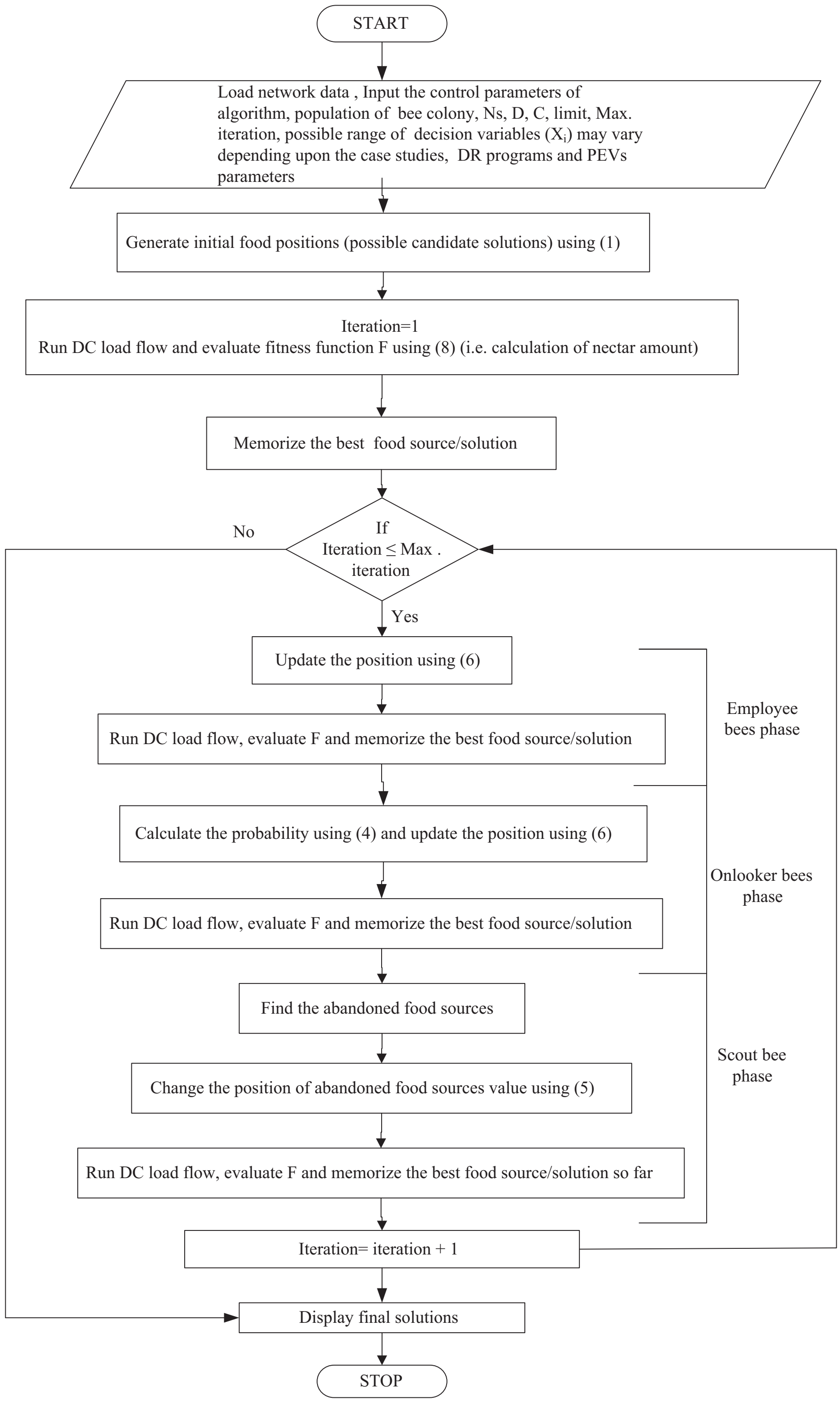

Fig. 1. Flow chart of GABC algorithm for the proposed STNEP problem.

Selection of the control parameters of the GABC algorithm

The GABC algorithm has five input parameters, and these parameters are highly sensitive to the output. These parameters also depend on the model under study. Hence the tuning of these parameters is important. The number of population (=colony size) (*Ns*), employed bees, onlooker bees, scout bees and C are the control parameters of the GABC algorithm. In order to set them carefully, 10 trial runs are taken on each one of them. The employed bees are considered as 50% of the colony size. The control parameter variation of the algorithm for scenario-1 is presented in Table 4.

The effect of colony size on transmission line investment cost is studied by varying colony size from 20 to 300 by keeping the limit value at 4, the value of *C* at 1.5 and onlooker bees = 30* employed bees. It is observed from Table 4 that as the colony size is increased the rate of achievement of the optimal solution is increased. However, to achieve less computational time its moderate value

Table 1
Generator characteristics [52].

Unit	Max., generation (MW)	a_i (\$/(MW)^2 h)	b^i (\$/MW h)	c_i (\$/h)	d_i (\$/h)	e_i (rad/MW)
1	80	0.10908	39.5804	950.606	25	0.0178
2	130	0.12111	39.5104	800.705	30	0.0168
3	240	0.10587	46.1592	451.325	20	0.0163
4	300	0.03546	38.3055	1243.531	20	0.0152
5	340	0.02803	40.3965	1049.998	30	0.0128
6	470	0.0211	36.3278	1658.569	60	0.0136

Table 2
Data of IEEE 24-bus system.

Bus number	G0 (MW)	G1 (MW)	G2 (MW)	G3 (MW)	G4 (MW)	Load Pd (MW)	Modified generator cost characteristics
1	576	576	465	576	520	324	Unit (5)+ Unit (3)
2	576	576	576	576	520	291	Unit (5)+ Unit (3)
3	0	0	0	0	0	540	–
4	0	0	0	0	0	222	–
5	0	0	0	0	0	213	–
6	0	0	0	0	0	408	–
7	900	900	722	900	812	375	3*Unit (4)
8	0	0	0	0	0	513	–
9	0	0	0	0	0	525	–
10	0	0	0	0	0	585	–
11	0	0	0	0	0	0	–
12	0	0	0	0	0	0	–
13	1773	1773	1424	1457	1599	795	3*Unit (5)+ Unit (1)
14	0	0	0	0	0	582	–
15	645	645	645	325	581	951	Unit (5)+ Unit (1)+ Unit (3)
16	465	465	465	282	419	300	Unit (6)
17	0	0	0	0	0	0	–
18	1200	1200	1200	603	718	999	4*Unit (4)
19	0	0	0	0	0	543	–
20	0	0	0	0	0	384	–
21	1200	1200	1200	951	1077	0	4*Unit (4)
22	900	900	900	900	900	0	3*Unit (4)
23	1980	315	953	1980	1404	0	3*Unit (6)+ Unit (5)+ Unit (3)
24	0	0	0	0	0	0	–

Table 3
Details of wind generator and PEVs parameters.

Wind generator [53]	Cut-in speed = 4 m/s d_w = 8 US \$/MW h	Cut-out speed = 20 m/s k_p = 6 \$/MW h	Rated speed = 12 m/s k_r = 8 \$/MW h
PEVs [36]	Maximum battery capacity = 25 kW h	Minimum battery capacity = 10 kW h	Average battery capacity = 15 kW h Inverter efficiency = 85%

is considered. A similar procedure is followed for the selection of onlooker bees by keeping other parameters fixed. The limit value is responsible for the scout bee production in the GABC algorithm. To see its effect on algorithm performance it is varied from 2 to 12. From Fig. 2, it is observed that for lower value of limit i.e. 2, the chance of finding the optimal solution is less and as its value is increased the chance of getting optimal solution is increased. But according to [58], for high limit value exploration capability of the algorithm is more, while with a very low value it reduces the exploitation capability. Hence, a moderate value is considered for this study.

From Fig. 2 it is observed that for very high value of C, the algorithm fails to find the optimal solution and for low value it can obtain the optimal solution but with a higher number of iterations. Therefore, in this study the value of C is taken as 1.5. From the graph, it is observed that at this value of C the GABC algorithm has good exploration and finds the optimal solution in less than 30 iterations. Figs. 3–5 portray the impact of colony size, onlooker bees and limit value variations in the total cost. It is seen that with the increase in colony size, the number of onlooker bees and limit value, the presented optimization algorithm yields the optimal solution in less number of iterations. To show the convergence performance of ABC and GABC algorithms, a graph is plotted for scenario 1 and it is as shown in Fig. 6. It is observed from the graph that the GABC algorithm reaches the optimal solution in less than 50 iterations while ABC algorithm takes more than 100 iterations for the same number of colony size (=50). Hence, this indicates that the modification made in the basic ABC algorithm is effective.

Based on the above trail runs the following control parameters are selected for the best solution of the GABC algorithm: population size (colony size) Ns = 50, Onlooker bees = 750, limit = 4, C = 1.5 and the maximum number of iterations = 500. The best result for minimum total cost TC with these control parameters is obtained after 30 trails.

Results

In these studies, scenarios 1–8 are analyzed on a modified IEEE 24-bus system and scenario-1 is analyzed on Brazilian 46-bus and Colombian 93-bus system. The capability of the GABC optimization algorithm is demonstrated and validated through simulation of the scenarios 1–8. The simulation results and generating units

Table 4
Control parameter variations of GABC algorithm (Scenario 1).

Control parameters	Result (INVC US					Computation time for 500 iterations, seconds
	Best	Worst	Average	Trial	Success	
20	390,000,000	472,000,000	390,000,000	10	4	259.228
50	**390,000,000**	**390,000,000**	**390,000,000**	**10**	**10**	**650.649**
100	390,000,000	390,000,000	390,000,000	10	10	1319.955
150	390,000,000	390,000,000	390,000,000	10	10	1927.209
200	390,000,000	390,000,000	390,000,000	10	10	2595.437
250	390,000,000	390,000,000	390,000,000	10	10	3251.680
300	390,000,000	390,000,000	390,000,000	10	10	3856.877
Onlooker bees						
125	390,000,000	506,000,000	413,200,000	10	8	130.660
250	390,000,000	390,000,000	390,000,000	10	10	246.722
500	390,000,000	390,000,000	390,000,000	10	10	475.122
750	**390,000,000**	**390,000,000**	**390,000,000**	**10**	**10**	**703.737**
1000	390,000,000	390,000,000	390,000,000	10	10	889.622
Limit value						
2	390,000,000	390,000,000	390,000,000	10	6	657.546
4	**390,000,000**	**452,000,000**	**402,400,000**	**10**	**8**	**646.869**
6	390,000,000	452,000,000	414,800,000	10	6	651.773
8	390,000,000	452,000,000	402,400,000	10	8	640.880
10	390,000,000	390,000,000	390,000,000	10	10	626.987
12	390,000,000	390,000,000	390,000,000	10	10	639.322

Bold values denote the optimal solution found.

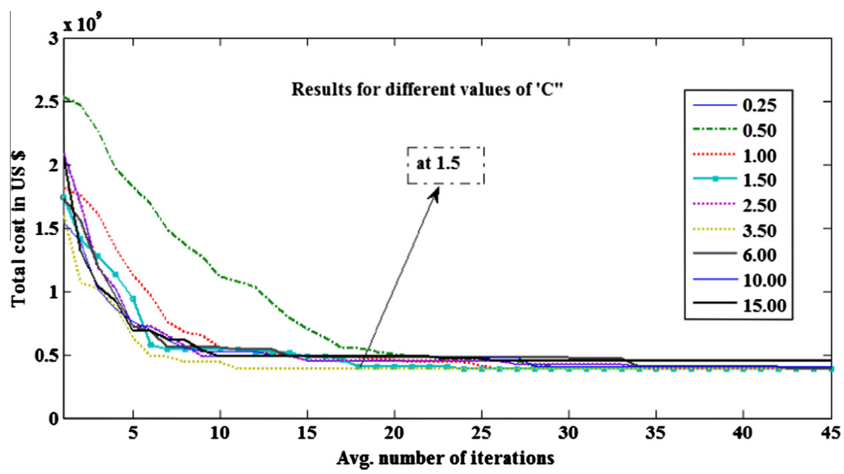

Fig. 2. The impact of different values of *C* (non-negative number) on Total cost.

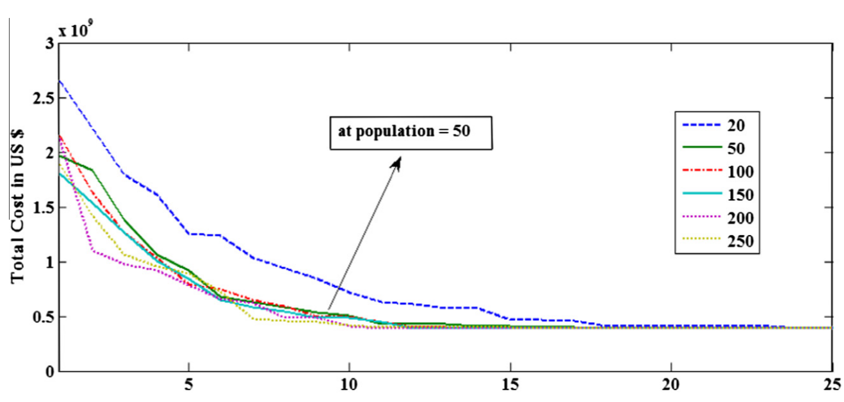

Fig. 3. The impact of variations of colony size on total cost.

scheduling for all the scenarios for IEEE 24-bus system are enumerated in Tables 5 and 6. The details of the PEVs power output and number of PEVs are presented in Table 7. Form Table 7, it is observed that the PEVs power output is reduced for scenario-8 as compared to scenarios 5–7. The comprehensive results for all the scenarios are described below:

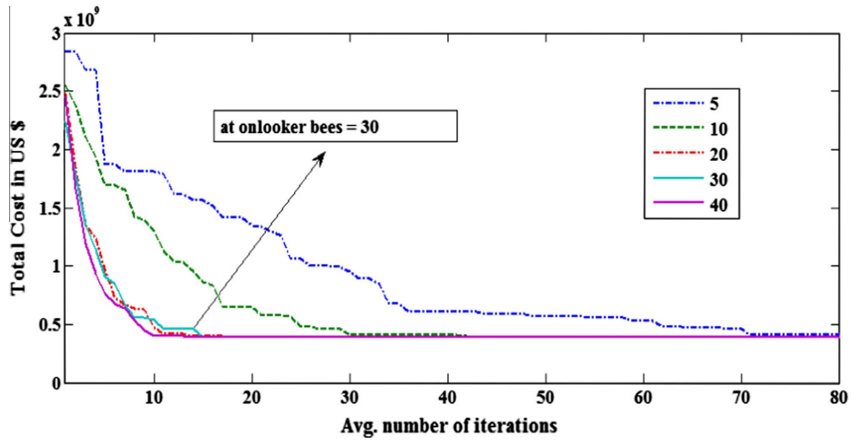

Fig. 4. The impact of variations of onlooker bees on total cost.

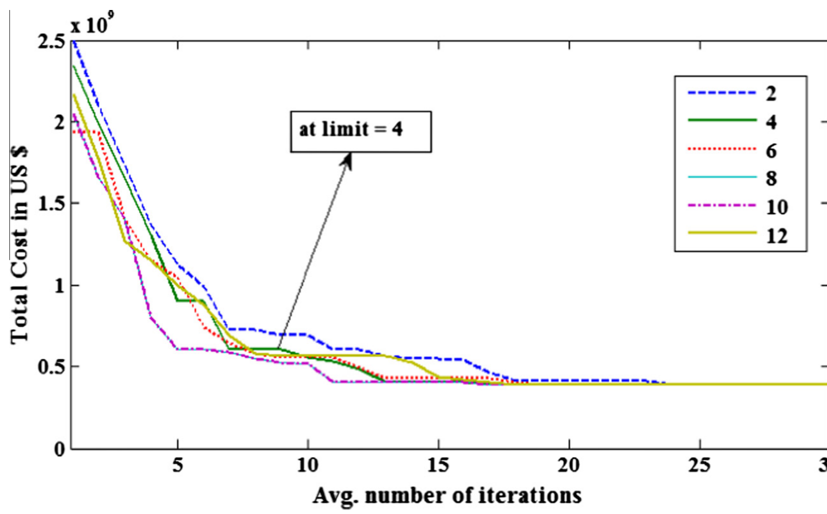

Fig. 5. The impact of variations of limit value on total cost.

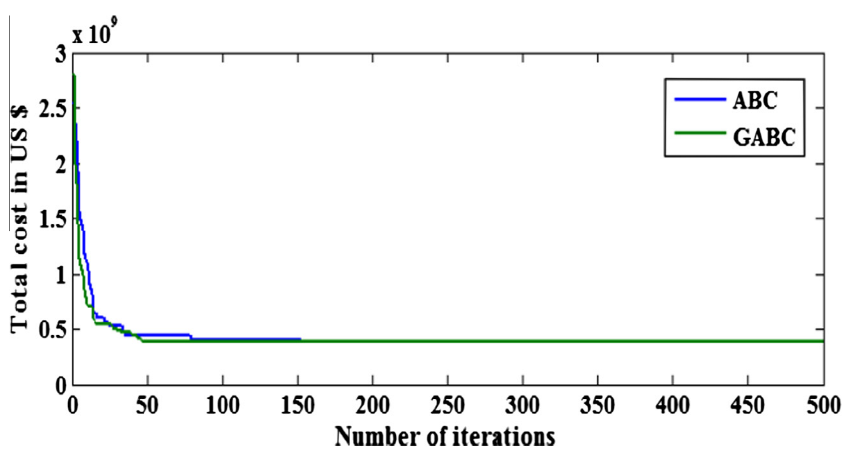

Fig. 6. Cost convergence comparison curve for ABC and GABC.

Scenario 1: In this scenario, the static TENP problem (8) is solved only with thermal generating unit. For IEEE 24-bus system simulation, generation plan G_1 is considered. In this case the transmission line investment cost (TLC) obtained with the GABC optimization algorithm is 390,000,000 US \$ with additions of 12 new lines to the base network and the added line network topology is: $n_{1-5} = 1$, $n_{3-24} = 1$, $n_{6-10} = 1$, $n_{7-8} = 2$, $n_{14-16} = 1$, $n_{15-24} = 1$, $n_{16-17} = 2$, $n_{16-19} = 1$ and $n_{17-18} = 2$.

For Brazilian 46-bus network the optimal solution obtained has TLC = 154,420,000 US \$ with additions of 16 new lines to the base

Table 5
Dispatch of generating units and PEVs for all scenarios of the proposed STNEP problem.

Scenarios	Generating Units (MW)												Total load at level 1 (MW)	Total generations (MW)
	P_{g1}	P_{g2}	P_{g7}	P_{g13}	P_{g15}	P_{g16}	P_{g18}	P_{g21}	P_{g22}	P_{g23}	P_{wind}	P_{PEV}		
1 Base Case	576.00	576.00	900.00	1773.00	645.00	465.00	1200.00	1200.00	900.00	315.00	–	–	8550.00	8550.00
2 With generation resize	570.42	570.89	900.00	1577.58	644.79	464.52	942.14	1189.33	65.54	1624.76	–	–	8550.00	8550.00
3 With EDRP-DR	576.00	575.03	884.06	1772.95	638.00	464.99	1200.00	387.06	172.78	1531.75	–	–	8202.65	8202.65
4 With wind uncertainty	573.62	573.62	552.79	1769.44	645.00	373.61	737.06	737.06	552.79	1694.48	340.50	–	8550.00	8550.00
5 With PEVs	574.44	574.44	553.24	1773.00	645.00	373.23	737.66	737.66	553.24	1694.14	–	333.82	8549.92	8550.00
6 With EDRP and PEVs	533.69	533.69	530.11	1773.00	612.80	369.91	706.81	706.81	530.11	1643.43	–	262.27	8202.65	8202.65
7 With wind uncertainty and PEVs	576.00	576.00	543.26	1700.03	578.87	306.61	724.35	724.35	543.26	1498.66	446.59	331.98	8549.99	8550.00
8 With EDRP and PEVs, with consideration of wind uncertainty	576.00	576.00	514.11	1765.71	642.72	243.69	685.48	685.48	514.11	1307.97	444.01	247.32	8202.65	8202.65

Table 6
Overall summary of results obtained for the proposed STNEP problem.

Scenarios	Results of STNEP									
	TLC, US $	Average, US $	Worst, US $	Standard deviation	FC, US $/hr	TWC, US $/hr	DRC, US $	PEVs cost, US $	TC, US $	Total new lines added
1 Base Case	390,000,000	390,000,000	390,000,000	0	–	–	–	–	**390,000,000.000**	**12**
2 With generation resize	152,000,000	169,400,000	184,000,000	12,580,408.048	–	–	–	–	**152,000,000.000**	**5**
3 With EDRP-DR	136,000,000	154,400,000	184,000,000	18,968,980.527	–	–	4,515.500	–	**136,004,515.500**	**5**
4 With wind uncertainty	136,000,000	143,400,000	172,000,000	1,5027,382.414	441,095.399	3,205.359	–	–	**136,444,300.758**	**4**
5 With PEVs	132,000,000	213,000,000	278,000,000	44,624,358.072	453,000.845	–	–	10,726.099	**132,463,726.944**	**3**
6 With EDRP and PEVs	128,000,000	122,400,000	156,000,000	19,995,555.062	430,834.350	–	4,515.500	5,788.283	**128,441,138.133**	**3**
7 With wind uncertainty and PEVs	104,000,000	125,400,000	156,000,000	21,869,308.783	435,666.742	3,595.132	–	8,790.282	**104,448,052.157**	**3**
8 With EDRP and PEVs, with consideration of wind uncertainty	100,000,000	108,400,000	128,000,000	1,1027,239.002	424,949.476	3,574.338	4,515.500	5,808.396	**100,438,847.709**	**3**

Table 7
Details of PEVs for scenarios 5–8 of the STNEP problem.

Load levels	Demand	Durations (h)	Scenarios							
			5 With PEVs		6 With EDRP-DR and PEVs		7 With wind uncertainty and PEVs		8 with EDRP and PEVs, with consideration of wind uncertainty	
			P_{PEV} (MW)	Vehicle number	P_{PEV} (MW)	Vehicle number	P_{PEV} (MW)	Vehicle number	PP_{PEV} (MW)	Vehicle number
1	**8550**	**0–400**	**333.824**	38,907	**262.271**	30,483	**340.502**	39,508	**247.327**	28,679
2	7695	400–900	317.062	36,748	358.091	41,498	348.925	40,498	245.745	28,499
3	6840	900–1500	436.888	50,699	421.389	48,899	417.296	48,599	344.734	40,199
4	5985	1500–2300	625.540	72,797	261.908	30,399	407.165	47,198	603.456	69,997
5	5130	2300–3100	−239.181	26,799	−346.277	38,799	−189.203	21,199	−414.105	46,398
6	5985	3100–4100	657.763	76,333	668.431	77,666	540.933	62,666	651.303	75,666
7	5130	4100–5100	−327.247	36,666	−419.471	47,000	−377.821	42,333	−380.796	42,666
8	4275	5100–6300	−239.185	26,799	−385.552	43,199	−392.691	43,999	−424.821	47,599
9	3420	6300–7500	−474.800	53,199	−496.219	55,599	−478.370	53,599	−431.961	48,399
10	2565	7500–8760	−421.700	47,249	−432.945	48,509	−562.266	62,999	−534.153	59,849

Table 8
Results of Brazilian 46-bus and Colombian 93-bus test systems for scenario 1.

Results of static TEP	Brazilian 46-bus test system Scenario 1	Colombian 93-bus test system Scenario 1
Best, US $	154,420,000	296,454,000
Average, US $	169,544,455	302,202,600
Worst, US $	179,702,000	338,744,000
Standard deviation	8,162,466.654	13,142,568
Computation for 500 iterations, s	794.353	3505.903

network and the added line network topology is: $n_{20-21} = 2$, $n_{42-43} = 2$, $n_{46-6} = 1$, $n_{19-25} = 1$, $n_{31-32} = 1$, $n_{28-30} = 1$, $n_{26-29} = 3$, $n_{24-25} = 2$, $n_{29-30} = 2$, and $n_{5-6} = 1$.

Similarly, for Colombian 93-bus network the optimal solution obtained has TLC = 296,454,000 US $ with additions of 5 new lines to the base network and the added line network topology is: $n_{50-54} = 1$, $n_{54-56} = 1$, $n_{55-57} = 1$, $n_{55-62} = 1$, $n_{56-57} = 1$. The simulation results with statistical analysis of the solution obtained for 46-bus and 93-bus is displayed in Table 8. The cost convergence curve for 46-bus and 93-bus is shown in Fig. 7. This curve portrays that the GABC optimization method is able to find the optimal solution within 100 iterations.

Scenario 2: In this case, for IEEE 24-bus system the optimal solution found by the GABC optimization algorithm has TLC = 152,000,000 US $ with additions of 5 new lines to the base network and the added line network topology is: $n_{6-10} = 1$, $n_{7-8} = 2$, $n_{10-12} = 1$ and $n_{14-16} = 1$.

Scenario 3: In this case, incentive-based (EDRP) DR program is applied to the proposed problem. This program offers maximum electricity price, incentive and penalty for the customers at the peak load level. For other load levels, incentive and penalty price offered is zero. The details of the DR program data are given in Table 9. The implementation of EDRP program results in the reduction of peak load to 8202.656 MW from 8550 MW and is shown in Fig. 8. The optimal solution has TLC = 136,000,000 US $, the cost of demand response participation (CDR) for peak load level = 4515.500 US $, TC = 136,004,515.500 US $ and following configuration: $n_{1-5} = 1$, $n_{6-10} = 1$, $n_{7-8} = 2$, and $n_{11-13} = 1$, with 5 new lines added to base network.

Scenario 4: In this case, the wind farm is installed at bus number 3 [20], which is a load bus. The maximum wind penetration of 450 MW is considered and is 5% of the total load connected. The optimal solution with wind power penetration has TLC = 136,000,000 US $, the fuel cost of the thermal generation units (FC) = 441095.399 US $/h, total wind power utilization cost as a summation of direct cost, overestimation cost, and underestimation cost (TWC) = 3205.359 US $/h and TC = 136,444,300.758 US $ with the line configuration: $n_{6-10} = 1$, $n_{7-8} = 1$, $n_{10-12} = 1$ and $n_{14-16} = 1$, with 4 new lines added to the base network.

Scenario 5: In this case, the PEVs are considered as a power source during peak hours and as load during rest of the hours by assuming all load buses to be the probable location to install PEVs. However, the minimum cost is achieved when it is installed at bus 8. The optimal solution with PEVs has TLC = 132,000,000 US $, FC = 453000.845 US $/h, the energy cost of the PEVs (ECV) = 10726.099 US $ and TC = 132,463,726.944 US $ with the line configuration: $n_{6-10} = 1$, $n_{10-12} = 1$ and $n_{11-13} = 1$, with 3 new lines added. The impact of PEVs on the load demand curve is shown in Fig. 8. This figure portrays that during the peak hours the load demand is reduced and in off-peak hours it is increased due to the integration of the PEVs. The charging/discharging coordination graph is presented in Fig. 9.

Scenario 6: The results found with EDRP program has TLC = 128,000,000 US $, FC = 430834.350 US $/h, CDR = 4515.500 US $, ECV = 5788.283 US $ and TC = 128,441,138.133 US $ with the line configuration: $n_{6-10} = 1$, $n_{10-12} = 1$ and $n_{13-14} = 1$, and 3 new lines added.

Scenario 7: The results found by the GABC algorithm in this case has TLC = 104,000,000 US $, FC = 435666.742 US $/h, TWC = 3595.132 US $/h, ECV = 8790.282 US $ and TC = 104,448,052.157 US $ with having network topology: $n_{1-5} = 1$, $n_{6-10} = 1$, and $n_{11-13} = 1$, with the addition of 3 new lines to the base network.

Scenario 8: The results found with the combination of the PEVs, wind power and EDRP program in this case has TLC = 100,000,000 US $, FC = 425338.630 US $/h, CDR = 4515.500 US $, TWC = 3574.338 US $/h, ECV = 5808.396 US $ and TC = 100,438,847.709 US $ with the line configuration: $n_{6-10} = 1$, $n_{10-12} = 1$ and $n_{13-14} = 1$ with addition of 3 new lines to the base network. The cost convergence curves for all the scenarios are shown in Fig. 10. This curve portrays that the GABC optimization technique can find the optimal solution within 100 iterations.

Discussion on the results

The results obtained with the GABC optimization algorithm are compared with the results available in the literature for scenarios 1 and 2 in order to prove its handling capabilities and are displayed

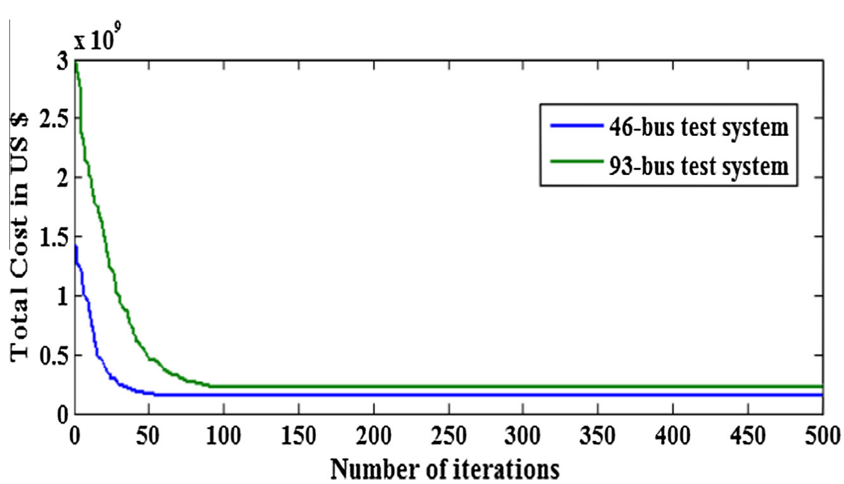

Fig. 7. Cost convergence curves for Brazilian 46-bus and Colombian 93-bus systems for scenario 1.

Table 9
Data for demand response program.

Load levels	1	2	3	4	5	6	7	8	9	10
% of original load	100	90	80	70	60	70	60	50	40	30
Duration (h)	400	500	600	800	800	1000	1000	1200	1200	1260
Elasticity	−0.10	−0.09	−0.085	−0.08	−0.075	−0.08	−0.075	−0.06	−0.05	−0.03
SP, US $/MW h	32	30	28	26	25	26	25	24	23	22
A (incentive), US $/MW h	16	0	0	0	0	0	0	0	0	0

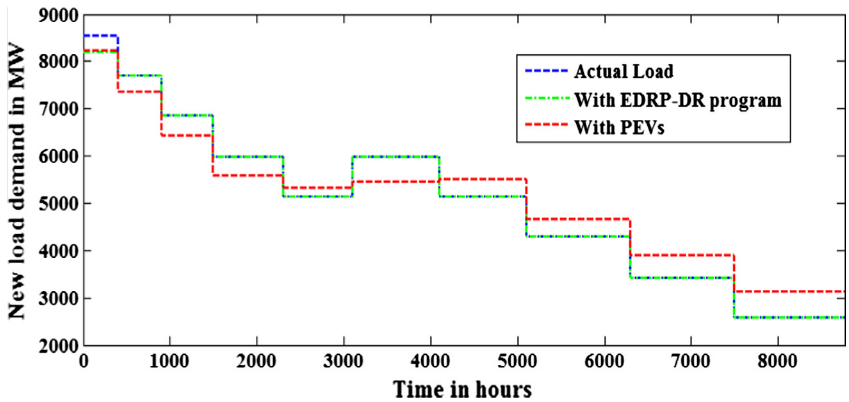

Fig. 8. Load curves with PEVs and demand response programs.

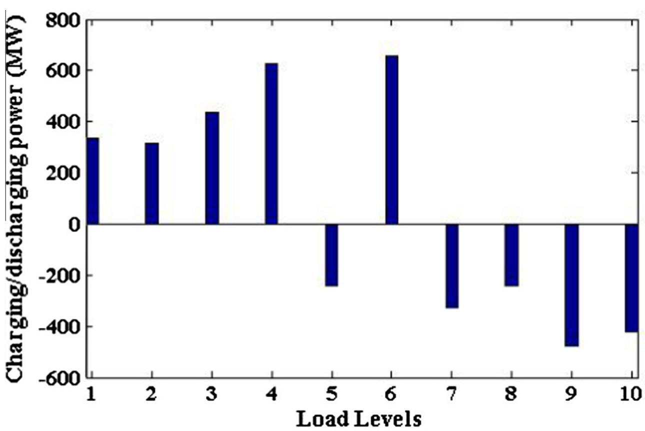

Fig. 9. Coordinated charging/discharging pattern of PEVs for Scenario 5.

in Table 10. As for the other scenarios results have been not reported in the literature. The major observations inferred from the studies are discussed below:

Scenario 1 and Scenario 2: For scenario-1, it is observed from Table 10 that for IEEE system, Brazilian system and Colombian system the GABC optimization technique performs better than other optimization technique such as CHA [39], CGA [12], DEA [12], and EGA [57]. For scenario-2, the GABC algorithm yields better results than the CGA [12], and New DA [50] techniques. However, the GABC technique can track the results yielded by HSA [15] and CBGA [51] optimization techniques. The resulting analysis indicates that it is suitable to adopt generation re-dispatch to achieve less transmission line investment cost. It is also observed from the results that for scenario-2, the GABC optimization technique has 61% reduction in the total system cost as compared to scenario-1.

Scenario 3: It is observed that with the implementation of EDRP program, the total cost obtained is found to be lesser than scenarios-1 and 2. The reduction obtained in total cost with the DR program is 65% as compared to scenario-1. From the load profile curves shown in Fig. 8, it is noted that by implementing the DR program, a new load demand for load level-1 gets reduced by 4% of the original peak demand i.e. 8550 MW. This implies that the DR program reduces the total cost and load demand of the system.

Scenario 4: It is observed that with the integration of wind power the total cost obtained is lower than scenarios-1 and-2 and has 65% and 10% reduction respectively. This indicates that the wind power penetration is helpful to minimize the total cost of the system. However, the transmission line cost obtained is same as that of the DR program case.

Scenario 5: In this case impact of the PEVs at a particular location is analyzed, and the effect on the total cost of the system is observed. The total cost obtained is found to be lesser than the above four scenarios. The integration of PEVs gives 65% reduction in the total cost as compared to scenario-1. From the load profile curves (Fig. 8), it is observed that load at the load level-1 gets reduced by 3.9%. This implies that both reduction in total cost and load demand of the system can be achieved with the integration of the PEVs to the system.

Scenario 6: In this case the combined effect of PEVs and DR program in the total cost is considered. The results indicate that the total cost, the fuel cost, the energy cost of the PEVs and the transmission line cost obtained is better than scenarios 1–5 with the combination of both the factors. The total cost is reduced by 67% as compared to scenario-1. The reduction in fuel cost is 2% as compared to scenario-4 and the energy cost of the PEVs is reduced by 46% as compared to scenario-5.

Scenario 7: In this case, both PEVs and wind power's uncertain nature follower impacts are analyzed in the total cost of the system. The results obtained indicate that the combination of wind power and PEVs reduces the total system cost, and it is found better than the above six scenarios. The amount of reduction obtained in the total cost is 73% as compared to scenario-1, in the fuel cost is 1% as compared to scenario-4 and in the energy cost of the PEVs is 18% as compared to scenario-5.

Scenario 8: The effect of PEVs, wind power and DR program on the total cost is evaluated in this case. The results illustrate that the total cost obtained is optimal among all other scenarios

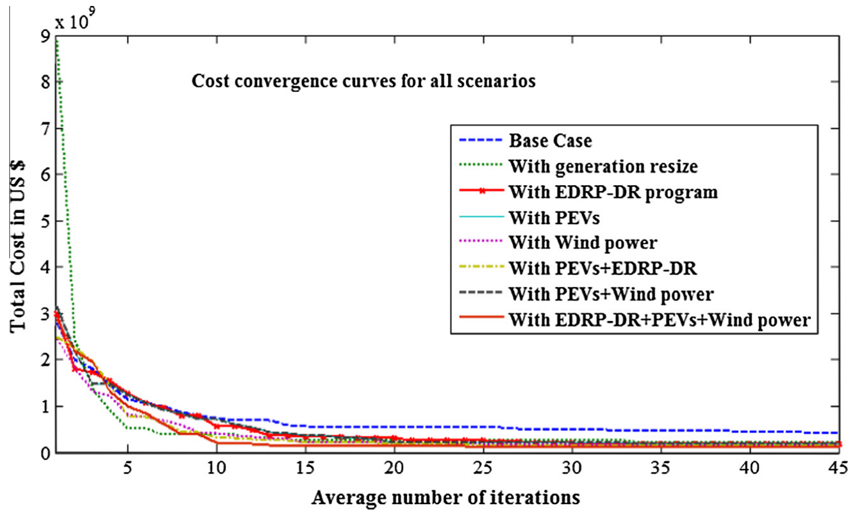

Fig. 10. Cost convergence curves of IEEE 24-bus system for all scenarios.

Table 10
Comparison of the proposed STNEP problem results for scenarios 1 and 2.

Methods	Optimal cost (US			
	IEEE 24-bus system		Brazilian 46-bus system	Colombian 93-bus system
	Scenario 1	Scenario 2	Scenario 1	Scenario 1
B&B [9]	———	152,000,000	154,420,000	———
DEA [12]	———	———	154,420,000	338,740,000
CGA [12]	———	———	162,598,000	———
HSA [15]	390,000,000	———	154,420,000	———
CHA [30]	438,000,000	———	———	———
New DA [50]	———	224,000,000	———	———
CBGA [51]	———	152,000,000	———	———
EGA [57]	———	———	———	316,440,000
GABC	**390,000,000**	**152,000,000**	**154,420,000**	**296,454,000**

Bold values denote the optimal solution found.

described above. The significant amount of reductions is observed in the total cost which is 74% in this case as compared to scenario-1. The fuel cost is reduced by 3% as compared to scenario-4 and the reduction in energy cost of vehicles is 45% as compared to scenario-5. This demonstrates the substantial impact of PEVs, wind power and DR program on the STNEP problem.

Conclusion

A complex cost model for static TNEP problem with the integration of wind power uncertainty and PEVs along with an incentive-based DR program is demonstrated in this paper. The total system cost is minimized by applying GABC optimization technique. A comparative analysis of the costs for the various combinations of these three factors is also presented. The three standard test systems are adopted to evaluate the robustness of the proposed method. The following are the main outcomes of all scenarios:

(1) The performance analysis indicates that the adopted GABC optimization algorithm yields better results than the other known solutions published in the literature.
(2) The implementation of DR program reduces the total demand of the system, which results in the reduction of the total cost of the system. Similarly, with the integration of wind power, the transmission line investment cost gets reduced. However, the total cost found with PEVs is better than the DR program and wind power.
(3) The results obtained with the combination of PEVs and wind has more impact on the total cost of the system as compared with the combination of PEVs and DR program. Particularly, the transmission line investment cost is found to be less.
(4) The performed studies demonstrate that with PEVs, wind power and DR program, the transmission line investment cost, the fuel cost of thermal generating units and the energy cost of the PEVs get reduced, which lowers the total cost of the system as compared to all other scenarios.
(5) The results obtained with GABC algorithm are competent and capable to handle the complex static TNEP problem. It is also observed from the cost convergence curves that the algorithm is able to find the optimal solution in less number of iterations.

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