Energy storage systems integrated transmission expansion planning

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The transmission network expansion planning is necessary for supplying the future needs, considering load growth. Furthermore, in restructured environments, transmission lines provide the required infrastructure for creating a competitive environment. In recent years, there has been a significant advancement in storage technologies. This advancement leads to using energy storage systems to postpone the construction or replacement of transmission lines. Therefore, in this paper, the problems of transmission expansion planning and energy storage systems deployment are investigated simultaneously. Considering the presence of storage devices and their effect on network operation cost, in this paper, the operation cost is modeled as an independent objective function along with investment cost. Moreover, the problems of transmission and storage expansion planning are modeled as a tri-objective optimization problem with the objectives of reducing costs and increasing the social welfare index in the power market. The multi-objective shuffled frog leaping evolutionary algorithm is used to solve these problems. The presented model for expansion planning is implemented and analyzed on IEEE 24-bus test system in the presence and absence of energy storage systems, and the effect of change in the price of energy storage systems is studied. The results of this research show that as the technology advances and the storage costs decrease, energy storage systems can play a pivotal role in reducing expansion planning costs of the power network and improving market-based indices in the restructured environment.

keywords: *Energy storage systems, Locational marginal price, Multi-objective optimization, Power market, Transmission expansion planning.*

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NOMENCLATURE

Sets

B Set of network buses
G Set of network power plants
LC Set of candidate corridors for constructing lines
E Set of energy storage systems (ESSs) of the network
T Set of time intervals

Parameters

$C_{l,y}$ Cost of constructing a line at corridor y ($\$/mile$)
r Annual interest rate
LT_e Lifetime of energy storage systems ($year$)
LT_l Lifetime of transmission lines ($year$)
$\overline{n_e}$ Maximum allowed number of ESSs at each bus
$\overline{n_l}$ Maximum allowed number of lines at each corridor
$\overline{P^{dis}}$ Maximum power discharge rate of ESS (MW)
$\overline{P^{ch}}$ Maximum power charge rate of ESS (MW)
P_{ESS} Rated power of an ESS unit (MW)
W_{ESS} Rated energy of an ESS unit (MW)
C_p Investment cost of ESS per MW ($\$/MW$)
C_w Investment cost of ESS per MWh ($\$/MWh$)
C_{ESS} Construction cost of an ESS unit with certain rated power and energy ($)
n_b Number of buses
n_g Number of generators
w_b Importance weight coefficient of bus b
$S(l)$ Indicator of the sending bus of Transmission line l
$r(l)$ Indicator of the receiving bus of Transmission line l
$\gamma_{(l)}$ Susceptance of line l

$\overline{f_l}$ Maximum power flow in transmission line l (MW)

$a_{i,t}, b_{i,t}$ Bidding coefficients of generator i during time interval t

ΔT Duration of time interval t (h)

$\underline{G_i}, \overline{G_i}$ Minimum and maximum output of generator i (MW)

FDT Full-power capacity discharge time of ESS (h)

Variable

$n_{e,b}$ Number of ESS units installed at bus b

$n_{l,y}$ Number of lines constructed at corridor y

$EH_{b,t}$ Energy of the available ESS at bus b at the end of time interval t (MWh)

$P^{dis}_{e,t}$ Discharged power of ESS e, at the end of time interval t (MW)

$P^{ch}_{e,t}$ Charged power of ESS e, at the end of time interval t (MW)

$\mathbf{LMP}_b$ Locational marginal price of bus b ($\$/MWh$)

$\overline{\mathbf{LMP}}$ Average locational marginal price of buses b ($\$/MWh$)

g_{bi} Power generation of bus i at peak load time (MW)

d_{bi} Load of bus i at peak load time (MW)

$P^{dis}_{b,t}$ Discharged power of the ESSs at bus b and time interval t (MW)

$g_{i,t}$ Output of generator i during time interval t (MW)

$P^{ch}_{b,t}$ Charged power of the ESSs at bus b and time interval t (MW)

1. INTRODUCTION

Optimal transmission expansion planning (TEP) has always been one of the most important issues in power system planning. In TEP, the objective is to expand the existing power system to serve the growing demand in the future and it has a vital role in the new electricity market because it should provide a nondiscriminatory environment for all market participants. Recent advances in material science make the large-scale deployment of electrochemical energy storage systems (ESS) in the transmission system a technically feasible option [1]. ESSs can have different applications in generation, transmission, and distribution sections of the power network. They can improve the performance of stressed power systems or systems with intermittent and unpredictable sources [2]. These systems can be helpful in load shifting [3], peak shaving [4], reducing operation and losses costs [5], power quality improvement and increasing reliability, network stability and penetration of renewable energy power plants, as well as voltage and frequency control [6, 7]. Moreover, large-scale energy storage systems can play a key role in decreasing or deferring the costs of network development and construction of new equipment [8]. Therefore, the TEP problem in the presence of ESS can change decision variables in a way that installing ESS can be an appropriate alternative for the construction or reinforcement of transmission lines to supply the future load. The most important obstacle in utilizing ESSs in the network is their high price, which will certainly decrease in the forthcoming years. Due to the increase in network needs, the growing penetration of renewable energy sources and the progress in the manufacturing technologies of ESSs, the penetration of ESSs in the network will increase [9]. In fact, it is expected that ESSs will play a key role as grid assets in the near future

Energy storage systems studied in existing literature can be divided into two categories: short term planning and long term planning. Most of the papers published on these topics focus on short term planning that integrated a dynamic response of ESSs and found the state of charge/discharge period of the predetermined storage unit [10–12]. Due to the load-displacement effect of ESSs, operation cost reduction is the main goal of these papers. On the other hand, long-term planning of ESS in the power network is much more complex because, in addition to operating costs and short-term studies, investment costs and long-term studies must also be considered [20]. Therefore, literature deals with transmission expansion planning in the presence of ESSs are very rare. Next, we review some of the related works.

Some papers have studied network expansion in the presence of ESSs in the traditional environment without taking network restructuring conditions into consideration [3, 13, 14]. In this researches, the main objective is to minimize investment and operation costs. In [3], transmission expansion planning is carried out in three steps, so the location, capacity, and the way of utilization of ESS are determined. In [13], renewable power plants are considered in the network and the effect of ESSs is investigated. In [14], only the investment cost is taken into account and TEP problem is only studied for peak load. Because of the uncoordinated optimization of system investments and operations, this planning is likely to lead to suboptimal transmission expansion plans.

Transmission expansion planning in the presence of energy storage systems in the power market environment is presented with the objectives of increasing revenue, increasing social welfare, and decreasing congestion of lines [9]. Ref. [12] have shown that the gain from using ESSs depends on their ownership, given the different incentives of each market player. Authors in [15] study the advantage of ESS from the independent system operator's and ESS owner's points of view. They show that if ESS placement is carried out simultaneously with network expansion, it can be economically beneficial for ESS owners. In [16], assume that ESSs are to be built and operated by transmission service providers and propose a mixed-integer linear programming (MILP) model integrating both investment and operation costs of lines and ESSs. In this model, the charging process of ESSs is not considered assumes that total energy capacity is considerably small and ESSs are always possible to be fully charged in off-peak hours.

In [17], a two-stage MILP model has been proposed to co-optimize investment and operation costs of lines and ESSs, using an hourly DC OPF formulation and show the benefit of having ESSs distributed throughout the network instead of having all of them concentrated in just a single node. In [18], ancillary markets make decisions on ESS placement in TEP to maximize their revenue, and it is shown that although investment cost of ESSs is high, their presence can increase social welfare. Furthermore, it is shown that since constructing a line can be very time-consuming and many problems can emerge during construction, using ESS can be very helpful in delaying the expansion of lines and decreasing investment costs. In [19], the economic and market-oriented effects of ESS are studied in network expansion problem in the presence of renewable energy sources and related uncertainties. In this paper, storage units are operated by a network planner and has been shown that the locational marginal price (LMP) significantly influences the optimal size and location of ESS.

In the existing literature, the issue of transmission and ESS expansion planning is modeled as single-objective problem and the objective function is usually minimizing the sum of investment and operation costs, but in the restructured power network, Given the important role of locational marginal prices in obtaining the optimal solution of line and ESS expansion planning, the effect of this index should be modeled as separate goal in the different objective function. For this reason, this paper proposes multi-objective modeling of the problem that simultaneously addresses economic and market-oriented goals.

In this paper, a practical model of the network power market is presented based on LMP and a new index is introduced to evaluate the level of social welfare. In contrast to the previously published papers, in this paper, to practically model the network and to provide the possibility of selecting an appropriate final solution, the problems of network expansion planning and ESS placement are modeled as a multi-objective problem, and the final solution is determined using fuzzy decision making approach.

A. Proposed methodology and contribution

This paper addresses the problem of network expansion in the power market environment. The proposed model is based on LMP in which at each network bus, the LMP determines the price of energy exchange at that particular bus. In previous studies, ESS owners' have had different positions, which could have different effects from the market participants' point of view. In the market model considered in this paper, a governmental organization (known as Tavanir) makes decisions on transmission and sub-transmission networks. This organization owns ESSs and is responsible for making a decision about them. In this paper, in addition to economic objectives, the market-oriented criterion is also considered as well as a new index is introduced to evaluate the level of social welfare.

Moreover, in contrast to performed studies in the past in which the problem of transmission expansion planning in the presence of ESS has been modeled as a single-objective problem, in this paper, the problem is modeled as a multi-objective problem and each objective is optimized separately and independently. Due to the presence of ESSs in the TEP problem and its effect on operation cost, in this paper, network operation cost is also taken into account in modeling in addition to investment cost. Considering the different variation ranges and scales of operation and investment costs, in papers that take the operation cost into account, a scaling coefficient is used to add this cost to the network cost function [21]. However, in this paper, in order to accurately model ESSs and to further investigate their role, operation cost is considered as an independent objective. Therefore, the proposed model consists of three objectives, i.e., decreasing investment cost, decreasing operation cost, and increasing the social welfare index. Considering the proposed modeling approach, the most appropriate method for solving the problem is to use multi-objective optimization algorithms. In this approach, a set of non-dominated solutions is presented as the Pareto-optimal front and based on the planer's opinion, each of the solutions of this set can be selected as the final solution of the problem. In this paper, the problem of interest is studied on the standard 24-bus IEEE test system and the multi-objective shuffled frog leaping algorithm is used to solve the problem. Finally, the best-compromised solution is obtained using a fuzzy decision making approach.

The most important contributions of this paper are as follows:

- Unlike in [3, 13, 14] that joint transmission and ESS expansion planning in the conventional environment, this paper model the problem in the LMP-based power market.
- ESSs have the potential to reduce energy and so reduce power system operation costs. Given the different incentives of each market player, Using ESS can be beneficial for their owners or not. Consumers benefit from energy price reductions, but generation firms (GenCos) reduce their profits if prices drop. [12] Shows that a combination of ownership for ESSs between GenCos and consumers may maximize social welfare in decentralized markets. So this paper defines a new index to evaluate the level of social welfare and because of its significant effect on the optimal solution, a separate objective function is considered for it.
- Considering the different variation ranges and scales of operation and investment costs, in this paper, in order to accurately model ESSs and to further investigate their role, operation cost and investment cost are considered as separate objective functions.
- [12–20] study the issue of transmission and ESS expansion planning in power market and consider only single objective function that usually minimize the sum of investment and operation costs but in this paper, given the important effect of market indices on final solution, a multi-objective modeling of the problem that simultaneously addresses economic and market-oriented goals in different objective function is presented.
- The presented multi-objective modeling is solved using an appropriate multi-objective optimization method. The proposed multi-objective algorithm has superiority in terms of accuracy and speed in comparison with other evolutionary algorithms. This is because of the parallel structure and memory-based mechanism of the algorithm [23] that is explained at the following.

B. Paper structure

This paper is structured as follows. In Section 2, mathematical model of the problem is presented. In Section 3, the optimization algorithm for solving the problem is introduced. In Section 4, simulation results of the problem are obtained and analyzed for different cases and to evaluate the validation of results, they compared with NSGA output. Finally, Section 5 concludes the paper.

2. MODELING THE PROBLEM

A. Energy storage systems and their costs

Energy storage systems can have different applications in a network; depending on these applications, they can have different types, technologies, technical specifications, and different costs. The investment cost of an energy storage system depends on its power capacity (P_{ESS}) and energy capacity (W_{ESS}), and it is calculated using the following equation [22].

$$C_{ESS} = C_P \times P_{ESS} + C_W \times W_{ESS} \tag{1}$$

In this equation, C_P depends on the cost of power converter system and the cost of connecting the unit to the network. Moreover, C_W is the investment cost for storing one MWh of energy in $\$/MWh$. Considering rated full-power capacity discharge time (FDT), the relationship between power and energy capacity is obtained as follows:

$$W_{ESS} = FDT \times P_{ESS} \tag{2}$$

Thus, the investment cost of an ESS unit with rated power of P_{ESS} is calculated using the following equation:

$$C_{ESS} = (C_P + C_W \times FDT) \times P_{ESS} + (C_P + C_{PC}) \times P_{ESS} \quad (3)$$

Depending on the type of energy storage and its manufacturing technology, the values of C_P, C_{PC} and C_W may be different.

B. Modeling objective function

B.1. Investment cost

Based on the discussion presented earlier in this paper, the cost of any transmission expansion planning can consist of two parts; investment cost of constructing a new line and ESS installation cost. Since the lifetimes of line and ESS are usually different, the sum of annualized costs is used to calculate the investment cost. The investment cost objective function is as follows [13]:

$$\min f_1 = \mathrm{K_1} \sum_{y \in \mathrm{LC}} \left(\mathrm{C_{1,y}} \times n_{l,y} \right) + \mathrm{K_e} \sum_{b \in \mathrm{B}} \mathrm{C_{ESS}} \times n_{e,b} \quad (4)$$

where C_{ESS} is a function of the rated power and energy of the device, K_l and K_e are the coefficients that convert the investment costs of line and ESS into per year values, which are calculated using the following equation:

$$\mathrm{K_1} = \frac{\mathrm{r(1+r)^{LT_1}}}{\mathrm{(1+r)^{LT_1}} - 1} \quad (5)$$

$$\mathrm{K}_e = \frac{\mathrm{r(1+r)^{LT_\mathit{e}}}}{\mathrm{(1+r)^{LT_\mathit{e}}} - 1} \quad (6)$$

B.2. Operation cost

The perspective presented for solving the problem is a long-term planning horizon, however, considering the presence of ESSs in the network and their effect on the costs of short-term planning, the network operation cost and the generation cost of power plants are also modeled in the problem. Despite the fact that operation and investment costs are of the same kind, due to their different scales and variation ranges, considering them in one single objective function causes the effect of one of the objective functions (the objective with lower scale and variations) to be weakened, and this results in an approximation in modeling the problem. Therefore, in this paper, to achieve accurate modeling, the operation cost is considered as an independent objective function.

The operation cost of power plant units is a function of their generation and bidding coefficients presented by power plants owners. Under such conditions, the objective function of minimizing the network operation cost in a particular period (one year) is calculated using the following equation:

$$\min f_2 = \left(\sum_{t=1}^{\mathrm{T}} \sum_{i=1}^{\mathrm{n_g}} g_{i,t} \times \left(\frac{1}{2} a_{i,t} \times g_{i,t} + b_{i,t} \right) \right) \quad (7)$$

In order to include the effect of an ESS on network operation cost, considering the model of the power market used, the power generated by the ESS (discharge state) is subtracted from the network load, and the consumed power (charge state) is added to the network load.

B.3. Standard deviation of locational marginal prices

In nodal pricing, all the customers trade electricity at the locational marginal price of the bus at which they are located. To create an environment in which all customers trade electricity at the same price, node prices must be equalized. A smaller difference between LMPs of buses results in lower discrimination encountered by the customers while trading electricity, and consequently, results in a facilitated competition. To measure the degree of competitiveness of the power market, a criterion called "the standard deviation of locational marginal price" is introduced. This index is defined as follows:

$$\sigma_{LMP} = \sqrt{\frac{1}{\mathrm{n_b} - 1} \sum_{b \in \mathrm{B}} \left(LMP_b - \overline{LMP} \right)^2} \quad (8)$$

where LMP_b represents the Lagrange coefficients or the shadow prices of load flow constraints at bus b, which is obtained from the optimal power flow (OPF) for a certain level of load; $\overline{LMP}$ is the average of LMP of buses, which is obtained using the following equation:

$$\overline{LMP} = \frac{1}{\mathrm{n_b}} \sum_{b \in \mathrm{B}} LMP_b \quad (9)$$

The lower the standard deviation of LMP, the smaller the difference between the marginal prices of buses, and as a result, the larger the competitiveness and social welfare level. Due to the limitation in the budget of transmission expansion for a certain budget, it is rational to provide a competitive environment for a larger number of customers. Therefore, the weighted standard deviation of the locational marginal price is proposed as one of the objectives. The objective function of interest is given as follows:

$$\min f_3 = \sqrt{\frac{1}{n_b - 1} \sum_{i=1}^{n_b} W_i \left(LMP_i - \overline{LMP} \right)^2} \quad (10)$$

where W_i represents the weight and importance of a bus, which is equal to the sum of generated and consumed powers at that bus.

$$W_i = g_{bi} + d_{bi} \quad (11)$$

C. Constraints

$$\sum_{i \in \mathrm{G_b}} g_{i,t} - \sum_{(l|s(l)=b)} f_{l,t} + \sum_{(l|r(l)=b)} f_{l,t} + \eta^{\mathrm{dis}} \times p_{b,t}^{dis} - \frac{1}{\mu^{\mathrm{ch}}} \times p_{b,t}^{ch} = d_{b,t}, \forall b \in \mathrm{B}, t \in \mathrm{T} \quad (12)$$

$$f_{l,t} - \gamma_l \left(\theta_{s(l)t} - \theta_{r(l),t} \right) = 0 \quad \forall l \in \mathrm{LC}, t \in \mathrm{T} \quad (13)$$

$$\left| f_{l,t} \right| \le \overline{f_l}, \quad \forall l \in \mathrm{LC}, t \in \mathrm{T} \quad (14)$$

$$\underline{\mathrm{G_i}} \le g_{i,t} \le \overline{\mathrm{G_i}}, \forall i \in \mathrm{G}, t \in \mathrm{T} \quad (15)$$

$$\sum_{b \in \mathrm{B}} \sum_{t=1}^{24} \left(\eta^{\mathrm{dis}}, p_{b,t}^{dis} - \frac{1}{\mu^{\mathrm{ch}}} p_{b,t}^{ch} \right) = 0 \quad (16)$$

$$n_{e,b} \le \overline{\mathrm{n_e}}, \forall e \in \mathrm{E}, b \in \mathrm{B} \quad (17)$$

$$n_{l,y} \le \overline{\mathrm{n_l}}, \forall y \in \mathrm{LC} \quad (18)$$

$$0 \leq P^{\text{dis}}_{e,t} \leq \overline{\text{P}^{\text{dis}}}, \forall e \in \text{E}, t \in \text{T} \tag{19}$$

$$0 \leq P^{\text{ch}}_{e,t} \leq \overline{\text{P}^{\text{ch}}}, \forall e \in \text{E}, t \in \text{T} \tag{20}$$

$$EH_{b,t} = EH_{b,t-1} + \left(\eta^{\text{dis}} \cdot p^{dis}_{b,t} - \frac{1}{\mu^{\text{ch}}} p^{ch}_{b,t}\right) \Delta T \quad \forall b \in \text{B}, t \in \text{T} \tag{21}$$

Constraint 12 shows the power balance at each bus of the network and includes the power injected by the power plant, the ESS and adjacent transmission lines. Based on the DC load flow model, Eq. 13 represents the power flowing through each line during any time interval and Eq. 14 shows the maximum allowed power of each line. Eq. 15 presents the constraints of the power generated by power plant units of the network. Eq. 16 expresses the balance between charge and discharge powers of each storage unit during a day. Eqs. 17 and 18 represent the maximum allowed number of ESS units at each bus and the maximum allowed number of lines at each corridor, respectively. Eqs. 19 and 20 show the charge and discharge limitations of each storage unit at tth time interval. Finally, Eq. 21 presents the energy of storage unit at bus b and time interval t.

3. OPTIMIZATION ALGORITHM

A. Multi-objective shuffled frog leaping algorithm

Shuffled frog leaping algorithm (SFLA) is an optimization approach that is inspired by the group behavior of frogs in search for finding the location with the maximum amount of food [15]. In this approach, the initial population is divided into several separate groups with the same number of members. The members of each group improve their locations in parallel through exchanging information with each other or the best member of the other groups.

Due to the classification mechanism of frogs and the parallel movement of the members of each group towards the optimum solution, a multi-objective shuffled frog leaping algorithm (MOSFLA) can have appropriate efficiency and speed in solving multi-objective optimization problems. In [23], this approach is investigated and its superiority over other multi-objective optimization methods is shown. The main steps of MOSFLA are described as follows:

a. Generating initial population: The initial population consisting of p frogs is generated randomly. Each frog represents a solution of the problem and includes a set of new ESSs. The ith frog is represented as $X_i = (x_{1,i}, x_{2,i}, ..., x_{d,i})$, where d is the number of network buses (for ESS installation).

b. Classification: At this stage, first the value of fitness functions is calculated for all members of the population, and a non-dominated sorting algorithm is used to sort the members [24]. Then, based on the sorted members, the population is divided into m groups with equal number of members in a way that each group consists of n frogs. Under such conditions, $p = m \times n$.

c. Archive mechanism: In the proposed optimization approach, an archive mechanism is used to keep the best solutions at each iteration. To do this, the solution that is not dominated by other solutions at each iteration is placed in front 1, is transferred to the archive and is then compared with the archive members. The best solutions that are not dominated by other existing solutions in the archive are kept and the rest are eliminated from the archive.

d. Local search: In each group, a local search process is carried out for a certain number of iterations. At each iteration, the position of the worst frog can be improved based on the position of the best frog in the group (X_b) and the best frog of all groups (X_g). If no improvement is observed, a new random position will be considered for the worst frog of the group.

In a local search process, the following steps are carried out at each iteration.

Step (1) the best and worst frogs in the group are determined and labeled as X_b and X_w, respectively.

Step (2) position of the worst frog of the group (X_w) varies according to the position of the best one in the group (X_b) as follows:

$$D^k = u.D^{k-1} + c.\text{rand}.(X_b - X_w) \tag{22}$$

$$X^{new}_w = X^{old}_w + D^k \tag{23}$$

where D^k is the leap size at the kth iteration of the algorithm and depends on the leap size in the previous iteration. Parameter u is the inertia weight that begins from an initial value and decreases gradually at each iteration of the algorithm.

$$u = \text{u}_{\max} - \frac{\text{u}_{\max} - \text{u}_{\min}}{\text{k}_{\max}} \times k \tag{24}$$

In the equation above, u_{max} and u_{min} are, respectively, the initial and final inertia weights, and k is the iteration counter of the algorithm; k_{max} represents the maximum number of iterations of the algorithm.

If the new solution dominates the previous one as expressed by the concept of domination in multi-objective optimization [24], the new frog replaces the previous one and the process goes to Step (5), otherwise Step (3) is executed.

Step (3) the best solution of all groups, X_g, replaces X_b in Eq. 22, and then using Eq. 23, a new frog is obtained. If an improvement is achieved in the solution, the new frog replaces the previous one and the process goes to Step (5), otherwise Step (4) is executed.

Step (4) a new frog is generated randomly, and replaces the worst frog of the group.

Step (5) the existing frogs in each group are compared with each other, are put in different fronts, and finally are sorted based on the front number.

Step (6) Steps (1) to (5) are repeated for a certain number of iterations (number of local search in each group).

e. Termination: Processes (b) to (d) are performed for a certain number of iterations (maximum number of iterations of the algorithm), and finally, the existing solutions in the archive are selected as the points of Pareto-optimal front, i.e., the set of final solutions of the problem.

B. Selecting best compromised solution

The final solution of a multi-objective problem is a set of solutions, which is called the Pareto-optimal front of the problem. Based on the planner's opinion, each one of the points of Pareto-optimal front can be selected as the best-compromised solution of the problem. In this paper, fuzzy decision making is used to select a solution from the Pareto-optimal front. In this approach, considering a fuzzy membership function and taking into account the desired values and importance level of each problem objective, a fuzzy membership value is assigned to each point of the Pareto front. Finally, the solution with the highest fuzzy value is selected as the best compromised solution of the problem [25].

C. Applying the proposed method for problem solving

This section describes the procedure of using the proposed optimization method for solving the problem of transmission line and ESS expansion planning. Fig. 1 shows the flowchart of the proposed algorithm. To solve this problem, first, the initial population is randomly generated with a certain number of feasible solutions (frogs). Then, for each frog, the objective functions of investment cost, operating cost and standard deviation of the LMP of buses are calculated. Next, with respect to the idea of domination in multi-objective optimization [24], frogs are compared with each other.

Frogs that are not dominated by any of other frogs (the best solutions) are placed in front 1, the frogs that are only dominated by the frogs of front 1 are placed in front 2, and this process continues till all frogs are apportioned to the fronts. Then, these frogs are sorted in ascending order, according to the front number. In each iteration, the frogs in front 1 are transferred to the archive and compared with the frogs there, and eventually, a new set of non-dominated frogs is selected and archived. In the next step, all frogs in each iteration (p), which are sorted based on the front number, are divided into m groups each of which contains n frogs, i.e., $p = m \times n$. The strategy of apportioning frogs to the groups is in such a way that the first frog is assigned to the first group, the second frog to the second group and the mth frog to the mth group. Moreover, (m+1)th frog is placed in the first group, and this continues until all p frogs are assigned to the m groups.

After classifying the solutions, local searches are performed in parallel for all groups. Accordingly, in each group, the best and the worst frog of the group is determined (according to the front number), and using Eqs. 22 and 23, the worst frog of each group moves toward the best frog. After this move, if the position of the worst frog is improved, the new position will override the current position; else, the same move will be repeated using the best frog of all groups (randomly selected from the archive). If the position of the worst frog does not improve, a random frog will be replaced. A local search is performed for all groups with a specified number of iterations, followed by an iteration of the whole algorithm. The proposed algorithm is executed with a specified number of iterations, and ultimately, the solutions in the archive are considered as the set of Pareto-optimal solutions of the problem. To choose the best-compromised solution of the problem, a fuzzy decision making method is used, and the process of problem solving is completed.

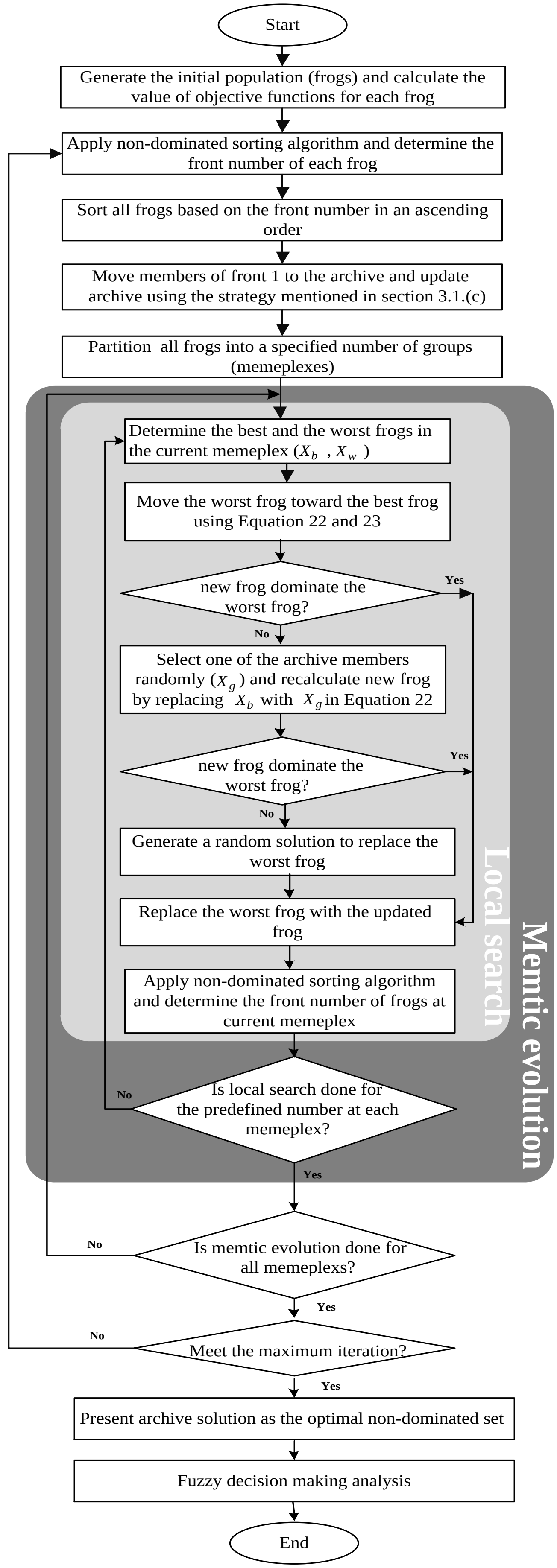

Fig. 1. Flowchart of the proposed algorithm.

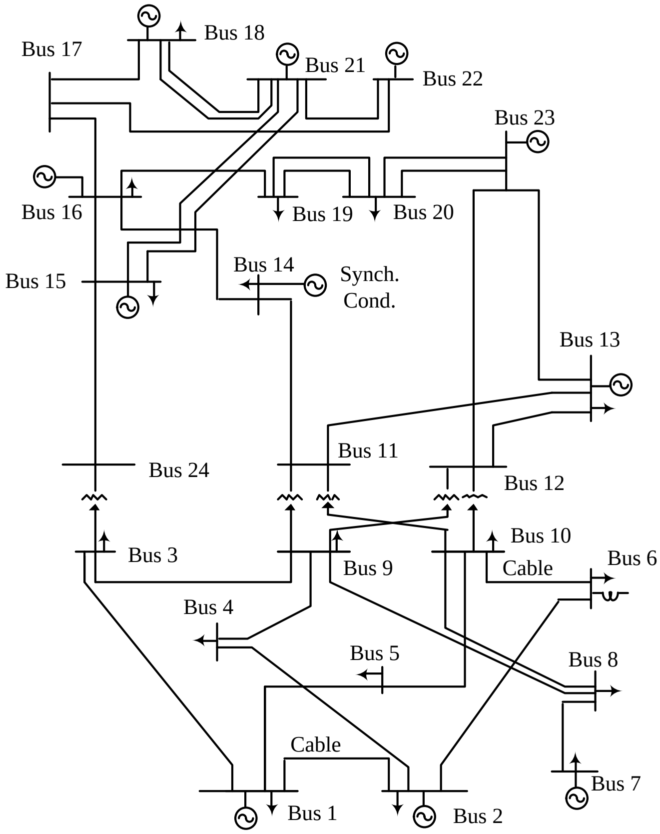

Fig. 2. IEEE 24-bus test system.

4. NUMERICAL RESULTS

A. Case study

The proposed model is implemented on the IEEE 24-bus test system using MATLAB software. Fig. 2 shows the single-line diagram of this network. Data of this network has been given in detail in [26]. Simulation results are obtained in MATLAB software environment using MATPOWER optimal power flow function [27] on a server with 64-bit Windows operating system, 16 GB of RAM and 12 cores with a processing speed of 2.2GHz.

Other important data of the test are as follows:

- Simulation is carried out for a 10-year network expansion planning, and the planning model is a static and single-step one.
- It is assumed that the system should be expanded for future conditions with the generation and load demand increased by 2.2 times their original values, i.e., load level of 6720 MW and generation level of 7490 MW. These conditions correspond to load incremental rate of 8% per year with a ten-year planning horizon [28].
- The capacity of each ESS unit is 20 MW and 80 MWh, and a maximum of three units can be installed at each bus. If batteries are used as storage systems, their investment cost is considered to be 200,000 $\$/MW$ and 25,000 $\$/MWh$ [29, 30]. Moreover, the charge and discharge efficiency of ESSs are considered to be 0.9.
- The candidate corridors for transmission expansion planning include 34 existing corridors and seven new ones for line construction, and a maximum of three lines are allowed in each corridor. The data related to the transmission lines has been presented in [31]. Construction costs of 138 and 230 kV transmission lines are between 200,000 and 2000,000 $\$/mile$, respectively [32–34]. However, in this paper, the construction cost of each line is considered to be 1000,000 $\$/mile$ [16].

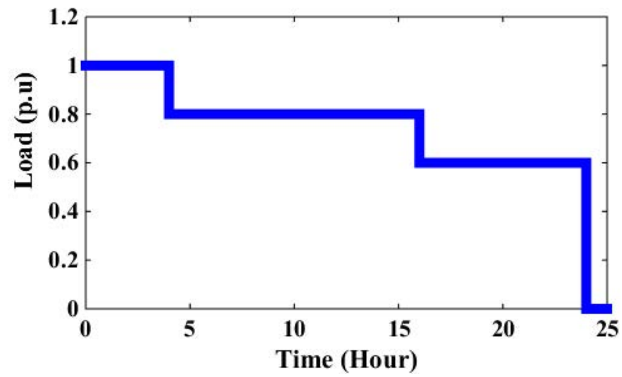

Fig. 3. Daily load duration curve.

- Lifetimes of ESSs and transmission lines are considered to be 10 and 20 years, respectively.
- To calculate the annual operation cost, daily load duration curves considered to be as depicted in Fig. 3.
- Parameters of the multi-objective shuffled frog leaping algorithm (MOSFLA) are obtained by using other literature data [23] and also trial and error method and they include:
  - The initial population size is 10 times the number of decision variables in each case.
  - The number of members of each group is equal to 5.
  - The number of local search processes performed in each group is equal to 3.
  - The initial and final inertia weights are considered to be 0.9 and 0.4, respectively.
  - Finally, the number of iterations of algorithm is considered to be 500.

B. Analyzing results

In this subsection, in order to investigate the effect of the existence of ESSs on the transmission expansion planning, the results of studying the network are presented and compared with each other in two different cases: (a) without considering ESSs (b) with considering ESSs. Taking the conditions in the previous subsection into account, the Pareto-optimal front includes 160 and 180 non-dominated solutions for cases (a) and (b), respectively. It is worth noting that, since it is difficult to show a set of non-dominated solutions in a 3D space, the numerical results are presented as two-objective conflict graphs, which are relative to each other. Therefore, in each graph, although the presented solutions may seem dominated, considering the third objective, which is not shown in the graph, it becomes clear that these solutions are non-dominated.

In Fig. 4, the amount of variations of operation cost in comparison to investment costs are shown for cases (a) and (b). By comparing the points of Pareto-optimal front in these two cases, the following results are obtained:

- The minimum investment cost of network expansion planning in which only lines are considered, is 4.9 M$, whereas by taking the presence of storage devices into account, the network load can be supplied with a lower investment cost (3.1 M$).
- In case (a), operation cost can be decreased to as low as 670 M$ and it does not change much more with the increase in investment cost. However, in case (b), due to the effect of the presence of storage devices, operation cost can be decreased to as low as 640 M$. This reveals the effective role of ESSs in decreasing network operation cost.
- The variation rate of operation cost versus investment cost is approximated by the slope of the linear curve. As can be seen, as the investment cost increases, the decreasing rate of operation cost in case (b) becomes greater than case (a) such that, in the first part, the slope of the linear curve in cases (a) and (b) are 11.74 and 12.49, respectively. This means that in this region, for each 1M$ of investment cost, the operation cost without and with storage devices decreases by 11.74 and 12.49 M$, respectively. Accordingly, investment in case (b) is more attractive and valuable than in case (a). However, as the investment cost increases, the variation rate of operation cost decreases, so the slope of the linear curve in the second part of cases (a) and (b) are equal to 0.81 and 1.83, respectively.
- Totally, Fig. 4 shows ESS can have a significant effect on short term costs. That's because, ESSs have the potential to move energy from peak to off-peak periods. Accordingly, power system operation costs can be reduced with an integrated operation of ESSs and power systems, where the presence of ESSs allows for a reduction in the use of some peaking units of the system.

Fig. 5 shows the variations of the total network cost versus investment cost in cases (a) and (b). The total network cost is in fact the sum of objective functions of operation cost and investment cost. As seen in this figure, with the increase in investment cost, the total network cost first decreases and then increases. Variations of the total network cost are due to the fact that, at first, with the increase in the investment cost, the operation cost decreases dramatically, and consequently, the total network cost decreases as well. Once the operation cost approaches its minimum value, its variations with respect to investment cost are insignificant. Therefore the total cost of network expansion will increase with the increase in investment cost. Furthermore, a comparison made between the two cases (a) and (b), which shows that the presence of ESS makes it possible to further decrease the total network expansion planning cost.

To investigate the effect of the presence of ESS on improving market indices of the power network, standard deviations of LMPs with respect to the amount of investment cost in two cases are considered. These cases, i.e., (a) network expansion in the absence of ESS, and (b), network expansion in the presence of ESSs, are compared with each other in Fig. 6. As is clear from this figure, in these cases, with the increase in investment cost, standard deviations of LMPs decrease, and as a result, the competitiveness of the network increases. However, since the slopes of the approximate linear curve in cases (a) and (b) are, respectively, 25.33 and 55.32, the decreasing variation rate of

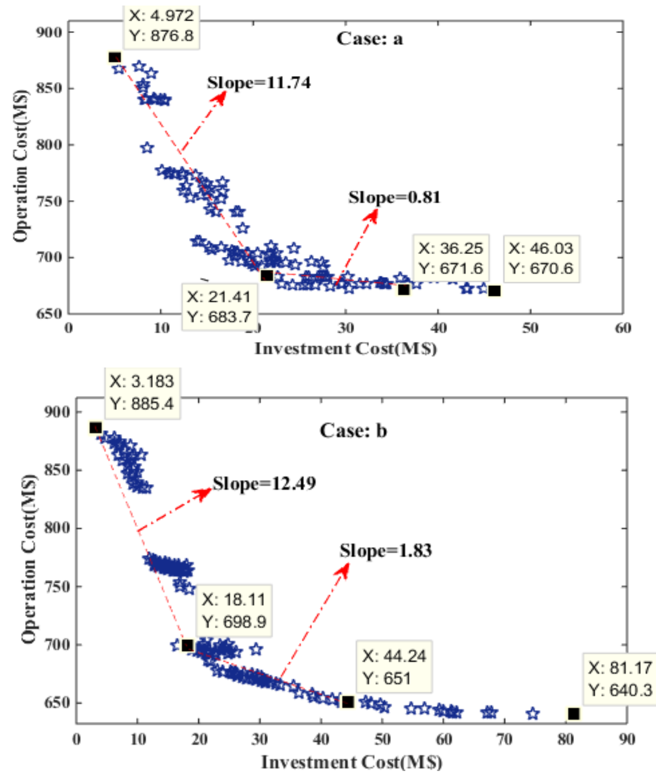

Fig. 4. Trade-off between operation and investment costs: (a) transmission expansion planning, and (b) transmission and ESS expansion planning.

standard deviations of LMPs in case (a) is much lower than case (b).

In fact, considering the approximated variations slope, for each 1 M$ of investment in the network, the value of standard deviation of LMPs decreases either by 25.33 $/MWh in the absence of ESS or by 55.32 $/MWh in the presence of ESS. Consequently, with a certain investment cost, competitive environment and the social welfare index increased in the presence of ESS. Moreover, it can be seen in Fig. 6 that the required amount of investment costs for network expansion with equal LPMs and a standard deviation of zero, in the presence and absence of ESS, are 29.53 M$ and 41.54 M$, respectively. Therefore, through the inclusion of ESS in a network, the competitive environment can be improved in the restructured environment with a lower investment cost.

The best solution for transmission expansion planning is selected by using the fuzzy decision making approach. In this way, all three objectives presented in this paper are taken into account simultaneously and with the same level of importance. The results related to new lines and the required ESSs in both cases (a) and (b) are shown in Table 1. A comparison between the results reveals that the presence of ESS causes a decrease in the number of lines requiring construction, and causes further improvement in the objectives of transmission expansion planning, including its total cost and standard deviation of LMPs, compared to the case in which no ESS is used.

C. Investigating effect of ESS price

As was discussed in the previous section, ESSs can have an effective role in transmission expansion planning. Despite all the advantages of using ESSs in power networks, their development and widespread application in the future are highly

Table 1. Best compromised solution by using fuzzy decision making

	Case a: Without ESS	Case b: With ESS
Corridor (number of added lines)	3-24(1), 6-10(1), 8-9(1), 9-11(1), 14-16(1), 15-21(1), 16-17(1), 20-23(1)	3-24(1), 8-9(1), 14-6(1), 15-21(1), 16-17(1)
ESSs (number of unit@node)	-	2@3, 1@4,1@5, 3@6, 1@10, 1@11, 1@13, 1@15,2@19,1@24
Total costs (annualed investment cost plus operation cost)	710.61	699.5
Standard deviation of LMP's	10	0

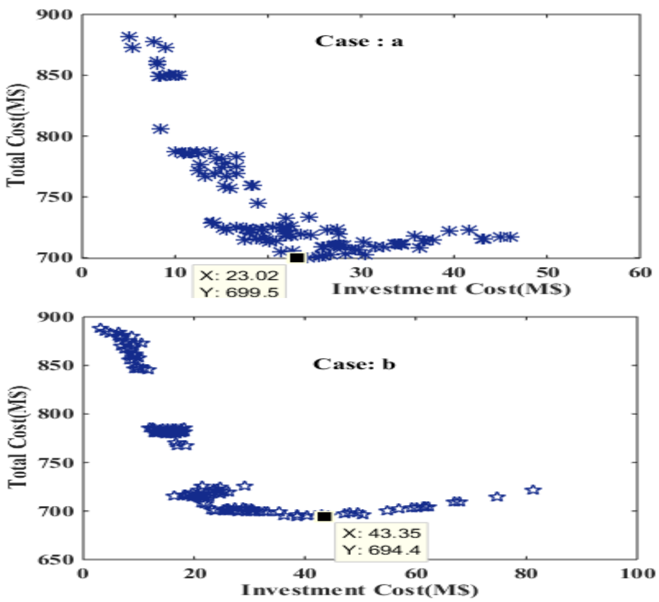

Fig. 5. Trade-off between total cost and investment cost: (a) transmission expansion planning, and (b) transmission and ESS expansion planning.

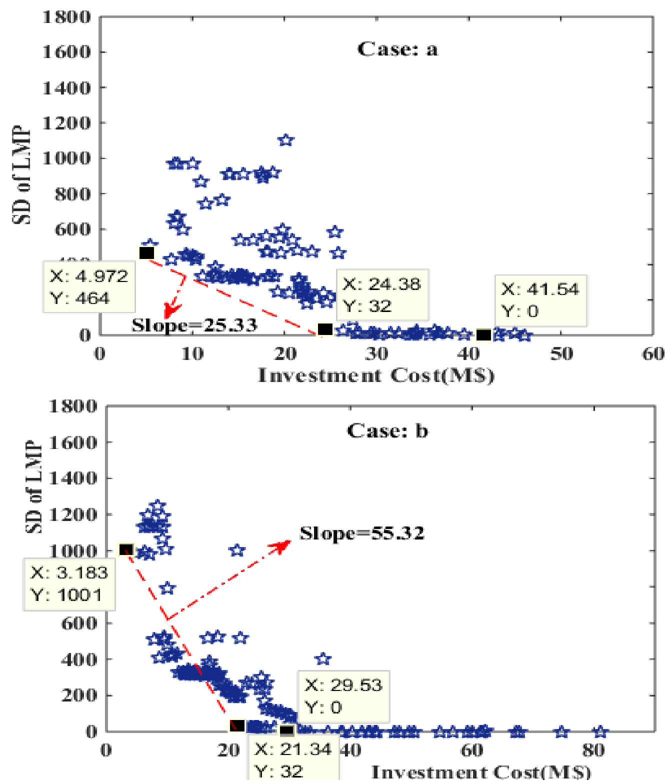

Fig. 6. Trade-off between the standard deviation of LMPs and investment cost: (a) transmission expansion planning and (b) transmission and ESS expansion planning.

dependent on their investment cost. According to the forecasts made in [29, 30], with the advances in technology, ESS price will decrease to as low as 200,000 \$/MW and 25,000 \$/MWh, until 2030. However, in this subsection, to take the uncertainty of ESS price forecast into consideration, the problem of transmission and ESS expansion planning is analyzed for different scale factors of ESS price. If the forecast price is obtained, the scale factor is 1, while for the failure in obtaining the forecast price, the scale factors 2 and 3 are taken into account. The obtained results of transmission and ESS expansion planning are compared with those of the TEP problem in which ESSs are not considered. To investigate and analyze the results, the values of different points of Pareto-optimal front are presented in Fig. 7. As can be seen in Fig. 7(a), the minimum investment cost required for network expansion varies with the increase in ESS price so that at lower ESS prices, their contribution to network expansion is higher and investment costs of network expansion are lower.

However, as the forecasted ESS price increases, their penetration in the network decreases. Accordingly, when the scale factor of ESS price is equal to 3, the minimum investment cost of network expansion in the presence and absence of ESSs are the same, i.e., in this case, due to the high price of ESSs, only lines are used for network expansion.

Moreover, network expansion results at the point with the lowest value of the standard deviation of the LMPs are presented in Fig. 7(b). As seen, the lowest value of the standard deviation of LMP in network expansion is zero, and at this point, the LMPs of all buses are equal. As can be seen in Fig. 7(b), with the increase in ESS price, the investment cost required for reaching this point has increased as well. However, the overall investment cost in the presence of ESS is lower compared to the case in which ESS is not present.

In Fig. 7(c), the points of the lowest operation costs are compared at different prices. As seen, in the presence of ESS, the lowest operation cost is 640 M\$, showing that, with the increase in ESS price, the optimal position and capacity of ESSs and lines have not changed, and consequently, optimal operation cost has not changed either. However, considering the increase in ESS price, the investment cost required to reach the point of minimum operation cost will be higher. In network expansion

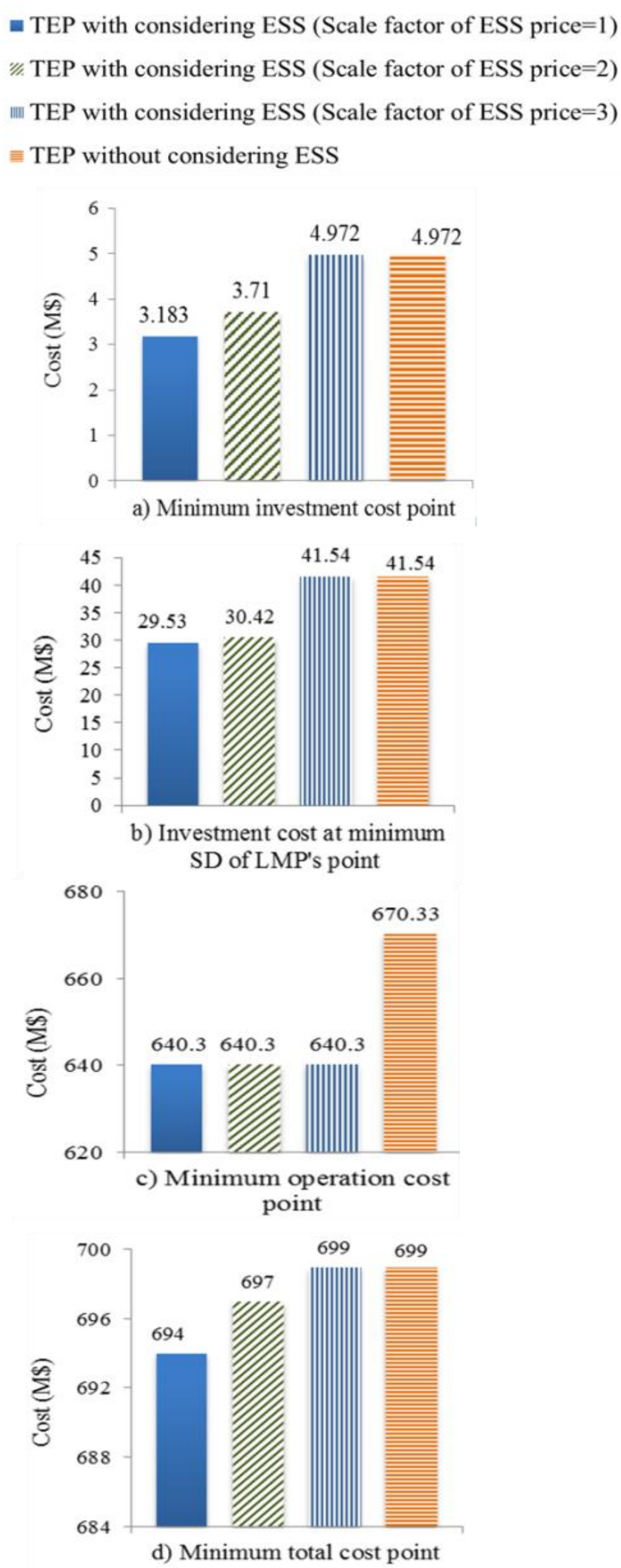

Fig. 7. Effect of ESS investment cost in the transmission and ESS expansion planning.

without considering ESSs, the operation cost increases and its lowest value is 670 M$.

In Fig. 7(d), the variation of the total network expansion cost (sum of investment and operation costs) with the increase in ESS price is shown. It is observed that, as the ESS price increases, the total network expansion cost increases as well, while it is lower in comparison to the expansion cost of the network in the absence of ESSs. Moreover, if the scale factor of ESS price exceeds 3, ESS cannot contribute to the network expansion, and the network expansion cost becomes equal to the case without ESS.

D. Validation of the proposed results

In this section, in order to verify the validity of the obtained solutions and to compare them with the results of another multi-objective algorithm, the problem of transmission line and ESS expansion planning is analyzed and solved for the IEEE 24-bus network using the non-dominated sorting genetic algorithm (NSGA). Required data of network and ESS are similar to section A. In order to implement NSGA, some required data, such as the initial population and the number of iterations of an algorithm similar to the proposed algorithm and other required parameters have been chosen from [24].

The results obtained using NSGA are shown in Fig. 8. As can be seen in the obtained optimal front in which both objectives are shown relative to each other, the lowest required investment and operation costs are, respectively, 6.2 and 651.9 (M$), and the smallest standard deviation of the LMP of buses is zero.

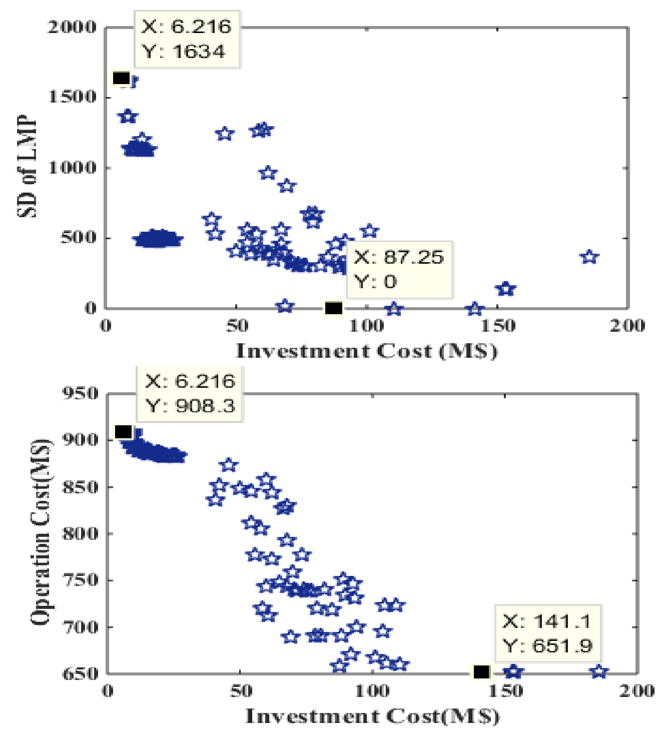

Fig. 8. Result of NSGA for transmission and ESS expansion planning problem.

To compare the results of NSGA and the proposed algorithm, Tables 2-4 present the details of network expansion planning at each minimum point of the objectives. As shown in the comparisons of these tables, the proposed algorithm has achieved better results. Furthermore, with regard to the smallest standard

Table 2. Minimum investment cost (M$) by using NSGA and proposed algorithm

	NSGA	Proposed algorithm
Corridor (number of added lines)	-	20-23(1)
ESSs (number of unit@node)	3@6, 3@19,2@20	1@6
Minimum investment cost (M$)	6.216	3.183

deviation of LMP, both methods have reached zero. However, by comparing Fig. 8 and Fig. 6(b), it is clear that the proposed method has achieved these results with a lower investment cost.

In addition to accuracy, the computational speed is one of the significant advantages of the proposed method over the NSGA and similar multi-objective methods. This is because in the proposed method, in all groups, local searches are performed in parallel and simultaneously, and cores of the server can be engaged in parallel. For this purpose, in the MATLAB software, parfor-loop is executed instead of for-loop in the local search of all groups, and this significantly increases the computational speed. The execution time of the proposed algorithm for each iteration is 42 seconds, while each iteration of NSGA takes 265 seconds. Therefore, according to the results, it seems that the proposed algorithm can be superior to other evolutionary methods in terms of accuracy and computational speed.

5. CONCLUSION AND FUTURE TRENDS

In this paper, the problem of ESS and transmission expansion planning in the network was addressed in order to supply the forecasted long-term demand. Network expansion planning was performed in an LMP-based power market environment to minimize the costs and to improve the social welfare index. Due to the fundamentally different scale and variation range of operation cost in comparison to the investment cost, in this paper, operation and investment costs were considered as separate objective functions, which results in more accurate and better modeling of the problem.

Standard deviation of the LMP of network buses was modeled as another objective function of the problem; minimization of this problem can result in an improvement in the social welfare index and competitiveness of the network. The problem model was solved accurately and completely using the multi-objective shuffled frog leaping algorithm. The results obtained from transmission expansion planning with and without considering ESSs were presented and compared with each other. The obtained results showed that if the price predictions are realized, ESSs can play a very effective role in decreasing investment and operation costs, increasing the level of competitiveness of the network and improving competition environment in the power market.

Considering the sensitivity analysis of ESS price, if the predicted price exceeds a certain level, the contribution of ESS in network expansion planning is decreased. However, taking various technical and economic advantages of ESSs into account, using them even with high prices might be justifiable, which is an issue that needs to be investigated in future works. Finally, aimed at validating MOSFLA result, the NSGA applied to solve the problem and showed that the proposed method had superiority in terms of accuracy and computational speed.

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Table 3. Minimum operation cost (M$) by using NSGA and proposed algorithm

	NSGA	Proposed algorithm
Corridor (number of added lines)	1-2(2), 2-6(2), 4-9(2), 5-10(1), 7-8(1), 9-11(2), 9-12(2), 10-11(2), 12-23(1), 13-23(2), 14-16(2), 15-21(2), 15-24(1), 16-17(2), 17-18(2), 2-8(2), 6-7(3)	2-4(1), 6-10(2), 7-8(1), 10-11(1), 11-13(1), 11-14(1), 12-23(1), 14-16(1), 15-21(1), 16-17(2), 17-18(1), 1-8(2)
ESSs (number of unit@node)	2@2, 3@3, 2@4, 3@6, 1@7, 1@10, 2@13, 2@17, 3@18, 1@19, 1@21, 3@22, 1@24	1@1, 2@2, 2@3, 1@4, 3@6, 3@8, 3@9, 3@10, 3@11, 1@14, 2@15, 1@16, 3@19, 2@20, 1@21, 1@22, 3@24
Minimum operation cost (M$)	651.9	640.3

Table 4. Minimum standard deviation of LMPs by using NSGA and proposed algorithm

	NSGA	Proposed algorithm
Corridor (number of added lines)	1-3(1), 3-24(2), 7-8(1), 9-11(2), 14-16(1), 15-21(2), 15-24(1), 16-17(1), 17-18(2), 21-22(1), 1-8(2), 19-23(1)	3-24(1), 8-9(1), 14-16(1), 15-21(1), 16-17(1), 20-23(1)
ESSs (number of unit@node)	2@6, 2@9, 2@14, 3@15, 3@17, 1@18	1@2, 1@3, 1@4, 3@6, 1@8, 1@20, 1@24
Minimum standard deviation of LMPs	0	0

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