Research Article – Vol. 01, Issue 02, No. 06

Advanced in Engineering and Intelligence Systems

Journal Web Page: https://aeis.bilijipub.com

Modeling and planning a transmission network expansion system in a regulated electricity market by considering demand-side management via a developed fuzzy-salp optimization algorithm

Yuying Zhang[1,*] , Lei Xu[1], Ji Li[1], Long Zhang[1],Zhi Yuan[2]

[1] *Electric Power Research Institute of State Grid Xinjiang Electric Power Co., Ltd., Urumqi, Xinjiang, 830011, China*
[2] *Engineering Research Center of Renewable Energy Power Generation and Grid-connected Control, Ministry of Education, Xinjiang University, Urumqi, Xinjiang, 830017, China*

Highlights

- A dynamic multi-objective TEP was performed based on the DB DR program and price-dependent bids.
- The TEP problem is a dynamic optimization problem with mixed and integer variables.
- The proposed algorithm was implemented on an IEEE 24-bus gird to display its benefits.
- Investment, congestion and load cut-off costs were selected as the objectives.
- Using DR reduced the investment cost and load cut-off by lowering the satisfaction level of investment cost.

Article Info

Received: 01 June 2022
Received in revised:02 July 2022
Accepted: 02 July 2022
Available online: 04 July 2022

Keywords

Multi-objective optimization;
Transmission network expansion;
planning (TEP);
Demand response (DR)

Abstract

With the daily rise in power demand, the penetration of dispersed generations (DG) such as wind turbines, the operation of series reactive compensator devices and the progress of reconfiguration in power system management, there is a dire need for optimally planning the expansion of transmission network lines. Transmission network expansion planning (TEP) is a major part of power system expansion planning that determines the type, location and time of installing new lines for the adequacy of power supply. Therefore, the TEP problem is a dynamic optimization problem with mixed and integer variables. In traditional systems, consumption management programs were used to overcome some problems of the power system. Meanwhile, demand response (DR) programs were discussed as a part of these programs. However, after the reconfiguration of power systems, these programs were gradually discarded due to incompatibilities with the nature of the market. Soon, due to the problems such as price instability, re-implementation of consumption management programs once again gained momentum. This time, these programs were altered to be compatible with the reconfigured power system management structure. This is widely accepted that increasing the presence and participation of consumers in DR programs in the electricity market will benefit not only individual consumers, but also the whole consumer community. In this paper, a dynamic multi-objective TEP is performed under reliability constraints in the market setting based on demand sales programs and price-dependent bids in the day-ahead market. The proposed algorithm was implemented on an IEEE 24-bus gird to display its benefits, including reduction of investment costs, mitigation of congestion and promotion of reliability.

Nomenclature

Parameters		S_{ij}^{max}	*Maximum transferable power from the line between buses i and j*
G	*Set of all generators*	$P_{dCR}^{i,max}$	*Maximum DB participating part in the ith bus*

* Corresponding Author: Yuying Zhang
Email: lj21sg@163.com

G_n:	*Set of generators connected to bus n*	$p_g^{i,max}$	*Maximum active power generated by the ith generator*
D	*Set of all loads*	$P_d^{i,max}$	*Maximum price taker part of the load in the ith bus*
D_n	*Set of loads connected to bus n*	$p_g^{i,min}$	*Minimum active power generated by the ith generator*
N_b	*Set of system buses*	P_d^i	*Minimum reactive power generated by the ith generator*
ψ	*Set of n-1 occurrences*	$VOLL_{dCH}^i$	*Price of the load proposing cut-off in the ith bus*
Variables		$VOLL_{dSH}^i$	*Price of the cut-off load in the ith bus*
p_g^i	*Active power generated by the ith generator*	c	*Price Factor*
d	*Bank discount rate*	a_g, b_g, c_g	*Price function coefficients of the generators*
G_{ij}	*Conductance of Line ij*	C_g	*Producers' cost function*
B_d	*Consumers' profit function*	α_{CR}^i	*Ratio of maximum load participating in DB to the price taker load of the ith bus*
A_i, B_i	*Coefficients of the load curve participating in the DR program in the ith bus*	P_{dDR}^i	*Responsive part of the load in the ith bus*
$p_{dSH}^{i,MN}$	*Cut-off part of the load in the ith bus when the line between m and n is cut-off*	q_g^i	*Reactive power generated by the ith generator*
P_{dPT}^i	*Price taker part of the load in the ith bus*	SW	*Social welfare*
p_{dSH}^i	*Cut-off part of the load in the ith bus*	$\lambda_{L,i}$	*Section associated with losses*
Q_D	*Demand Reactive power*	$\lambda_{C,i}$	*Section associated with congestion*
$Y_{ij} = G_{ij}$	*Elements i and j in the system admittance matrix*	α_{DR}^i	*Susceptance of Line ij*
Q_G	*Generator Reactive Power*	$SW_{WOC}^{N_y}$	*Social welfare in year NY without transmission constraints*
V_i^{min}	*Lower limit of voltage at bus i*	$SW_{WC}^{N_y}$	*Social welfare in year NY with transmission constraints*
$q_g^{i,max}$	*Maximum reactive power generated by the ith generator*	LCC_0	*Total cost of cut-off loads in normal operating conditions*
S_{ji}^{max}	*Maximum mixed power limit*	LCC_1:	*Total cost of cut-off loads in single-event operating conditions*
$P_{dDR}^{i,max}$	*Maximum responsive part of the load in the ith bus*	V_i^{max}	*Upper limit of voltage at bus i*

1. Introduction

Nowadays, with the growth in energy consumption, expansion planning has become critical and indispensable to supplying resources. Meanwhile, power system planning is a highly influential affair in the operation and repair of future power systems. In the past, power system expansion aimed to minimize investment of new equipment for power supply at an optimal level of reliability while meeting the operation constraints [1]. The formation of the electricity market added new objectives to the generation and transmission network expansion planning problem and converted it into a multi-objective, complex and large-scale problem. Traditional mathematical solution tools were no longer satisfying the needs of this new environment and had to be revised or changed, which led to the emergence of metaheuristic methods such as genetic algorithm (GA) or particle swarm optimization (PSO) algorithm [2]. These methods do not have the disadvantages of mathematical methods and use several stages to find final solutions, which reduces the risk of entrapment in local minima. Their advantages such as artificial intelligence, elitism and competitiveness ensure finding a final optimal solution with acceptable approximation to the absolute optimal point, albeit by increasing the computational volume [3]. Overall, power system planning problems are divided into static and dynamic groups. In the static planning, the location and capacity of new equipment are determined, while in the dynamic one, the installation time is also specified. In other words, in the static planning, design years are not dependent and are regarded as continuous, whereas in the dynamic one, each year is planned based on the equipment installed in the last years; planning of one year is not independent of other years [4]. In practice, power grid planning is performed dynamically. Although this feature complicates and prolongs calculations, it greatly helps improve the minimization of costs and optimization of the final solution. In regulated power systems, transmission network expansion planning (TEP) is traditionally discussed as an optimization problem aiming to minimize the costs of constructing new lines while maintaining reliability, while in the deregulated setting, TEP pursues different objectives [5]. The considerable effects of the generation and transfer sector on the reliability of power systems and its related heavy costs in operation and planning have motivated numerous studies.

In [6], an algorithm inspired by bats along with an efficient hybrid algorithm in the form of an efficient hybrid algorithm for TEP was proposed. This study considered network losses in extensive application in an actual large-scale system. In [7], a robust adaptive formulation was proposed which simultaneously displayed annual integration, investment decisions in capacity expansion lines, construction or cancellation of RES and conventional facilities. The dynamic transmission network and RES expansion problem was formulated as a three-level robust optimization problem. In [8], a TEP problem was dealt with to identify when and where new equipment such as transmission lines, cables and transformers had to be applied to the network. In [9], a novel framework was introduced for long-term generation and TEP in multi-carrier energy systems. Here, the studied system comprised a combined heat and power (CHP) system, a gas furnace, an electricity generation unit and transmission lines related to natural gas and electric grids. In [10], a framework of energy storage system (ESS) expansion planning studies in systems was proposed. The main objective was to find the optimal location and capacity of the dispersed ESS according to the system operator. In [11], the TEP problem was considered as a highly complex and mixed linear programming problem. The solution was essential for cost-effectively meeting the power demand. The gray wolf optimization (GWO) algorithm, which is a nature-inspired metaheuristic algorithm, was used for solving the problem. In [12], comprehensive examination of generation expansion planning was presented and it was shown that integration of demand-side management, ESS and short-term operational features of electricity power stations could markedly promote the flexibility of power systems and change energy generation and optimal capacity composition. In [13], a novel mathematical method was proposed for TEP and installation of battery ESS (BESS). An optimal location of small-scale BESS could help transfer systems in swarm management and improve power system security. BESS can also increase power system reliability in probabilistic conditions. The results demonstrated that a security and reliability approach to simultaneous TEP and optimal location of BESS could be beneficial. In [14], the increased penetration of RES units in far-away regions was dealt with. Due to fluctuations in RES generation, programming had to include operational decisions in the programming model. In [15], a risk-based expansion planning method was introduced. At the core of this method, there was an alternative current-based error model that simulated the power system reactions after probabilities. This method aimed to present an optimal expansion plan that paid attention to the balance between expansion costs and systemic failure risks. In [16], the generation expansion planning problem was solved by minimizing the total investment, operation, maintenance and unsupplied energy costs by using a modified frog jumping algorithm. In [17], a multi-objective generation expansion planning problem was solved which included pollution, operation and investment costs of new generators by using linear programming. In [18], the transmission expansion problem was solved by considering investment costs, reliability and congestion of lines, but disregarded the generation expansion planning problem. Moreover, this study calculated the mean load cut-off only in the case of a single-line outage. In [19], the line congestion costs were defined as the product of line transferred power by the difference in the local marginal prices (LMP) of buses on both ends. The total network congestion cost was calculated by summing the costs of lines and its reduction was pursued in selecting the optimal design. In [20], the congestion cost was defined as the difference in costs with and without transmission constraints. In [21], DR programs were modeled as virtual and dispersed resources for long-term distribution system expansion planning. In [22], the total costs of investment, losses and repair of transmission lines were minimized by considering the N-1 criterion for a single-line outage and solved it by using the honey bee evolutionary algorithm. In [23], the simultaneous expansion of generation and transmission capacities was solved to minimize the total costs of generators' fuel, fuel transfer, generator and line installation. In [24], a bi-level method was discussed. The first level dealt with the problem of transmission line expansion by the line operator. At the second level, the market revenue resulting from market clearing was solved based on game theory.

In Ref [25], using the states cooperation model of United State, a novel model is proposed for generation of renewable energy have been proposed. In [26], a novel two-level optimization model is proposed to achieve optimal energy value in hybrid energy systems contains renewable energy. In this proposed model the common benefits are considered as fitness function which is minimized the operation cost beside benefit maximizing. In [27], a risk-based model for distribution network planning considering demand response and bilateral contracts is proposed. A novel improved SOCP model to corporation between distribution and transmission network is proposed in [28]. In [29], an analyzed model for 2030 and 2050 years are proposed and the role of energy storage is illustrated in this work. Also, a novel technique based on Joint planning Expansion planning and placement of energy storage devices have been considered.

Accordingly, the current study proposes an overall framework for multi-objective dynamic TEP. The objectives are to minimize costs of investment and congestion while meeting system adequacy. Programming is performed in the market setting by foreseeing DR and using the AC model. To find the optimal Pareto region, a novel method based on the salp algorithm is proposed and the final decision is made by using the fuzzy method. It is assumed that transmission networks are managed and expanded by a regulatory institution (transmission provider) to maximize social welfare under reliability constraints. TEP is based on peak load because the transmission system must be able to operate correctly at the peak load. Problems such as congestion and mandatory load cut-off (due to shortage in generation or transmission constraints) often occur in the peak load. Moreover, DR is activated in peak hours when the market price rises. The market modeling, programming objectives, multi-objective optimization, the proposed algorithm and the results are presented below.

In the next section, the mathematical modelling of the study model is defined. In section 3, the objective function will be presented. The proposed improved optimization model can be achieved in section 4. Fuzzy modelling and simulation results are presented in sections 5 and 6, respectively and Finally conclusion of the proposed strategy is described in 7.

2. Market modeling

In deregulated power systems, the independent system operator (ISO) divided generators' generation such that the load is supplied with minimum costs while maintaining security and quality. In this section, the market-clearing mechanism is explained. This mechanism receives the bids of both demand and supply sides and includes the proposed constraints. This day-ahead market involves mixed bids and aims to maximize social welfare. Therefore, the operator must perform the optimization to determine the optimal generation and consumption programs, and obtain the market-clearing price. It is assumed that a limiting generation unit is used for clearing, so that the generators are encouraged to bid their actual costs.

2.1. Load model while considering DR

The accurate modeling of consumers' response to electrical energy price is essential. Figure 2 shows the demand and supply curves utilized in this study [31]. A part of demand (P_{dDR}^{max}) up to a certain value of lost load ($VOLL_{CR}$) is assumed to be price-responsive. In other words, this part participates in the market by making price-dependent bids. The other part (P_{dCR}^{max}) participates in the DB and directly proposes the cut-off bid at price $VOLL_{CR}$ to the market. Not all consumers have the ability or motivation to regulate their demands as a function of price; therefore, a part of this demand will remain. This part (P_{dPT}^{max}) is the price taker part that must be supplied at any price. Indeed, it is assumed that the system operator has a price limit equal to the value of lost load ($VOLL_{SH}$) which is the maximum momentary market price. Finally, the last part (P_{dSH}^{max}) cannot be supplied by the system, or since the price exceeds($VOLL_{CR}$), the operator intervenes by cutting off or reducing the fixed part of the loads. For any bus i, values ofP_{dDR}^{i}, P_{dCR}^{i} and P_{dSH}^{i} are determined in the optimization process conducted by ISO and we will have [3]:

$$p_d^i = \left(P_{dPT}^{i,max} - P_{dSH}^{i}\right) + \left(P_{dCR}^{i,max} - P_{dCR}^{i}\right) + P_{dDR}^{i} \tag{1}$$

2.2. Objective function for modeling the market

As noted, before, the objective is to maximize social welfare, i.e., the difference between the consumers' value for the purchased electrical energy and cost of generating this energy. The profit function or the consumers' value based on DR programs and cut-off load is [30]

$$\begin{aligned} B_d = \sum_{i\in D}\left(P_{dPT}^{i,max} - P_{dSH}^{i} \right) * VOLL_{SH}^{i} + \sum_{i\in D} P_{dDR}^{i} \ (A_i \\ + 0.5 B_i P_{dDR}^{i}) \\ + \sum_{i\in D}\left(P_{dCR}^{i,max} - P_{dCR}^{i}\right) * VOLL_{CR} \end{aligned} \tag{2}$$

The first term is the gross surplus of price-taker consumers. The term inside the parentheses in the first term shows the supplied price taker load. The second term is the price-responsive gross surplus of consumers and the third term is the DB-participating gross surplus load that is not cut-off. Moreover, $p_{dDR}^{i,\max}$ is often expressed as a ratio of the price taker load:

$$P_{dCR}^{i,max} = \alpha_{CR}^{i} P_{dPT}^{i,max} \tag{3}$$

$$P_{dDR}^{i,max} = \alpha_{DR}^{i} P_{dPT}^{i,max} \tag{4}$$

Coefficients α_{CR}^{i} and α_{DR}^{i} denote the ratio of DR participation in each bus per price taker's load price. In this paper, these coefficients are assumed to be 0.07 based on the US electricity markets. The generators' cost function is [31]:

$$C_g = \sum_{i\in G} \left(a_g^i p_g^{i2} + b_g^i p_g^i + c_g^i\right) + \sum_{i\in D} P_{dCR}^{i,} VOLL_{dCR}^{i} + \sum_{i\in D} P_{dSH}^{i,} VOLL_{dSH}^{i} \tag{5}$$

The first term is the generators' cost function and the second and third terms are the cost paid to cut-off DB and mandatory loads. The goal is to maximize social welfare, i.e.,

$$maxSW = B_d - C_g \tag{6}$$

2.2.1. Constraints

The constraints include [32]:

$$\sum_{i\in G_n} p_g^i - \sum_{i\in D_n} [(P_{dPT}^{i,max} - P_{dSH}^{i}) + (P_{dCR}^{i,max} - P_{dCR}^{i}) + P_{dDR}^{i}] - \sum_{j\in N_b} [G_{ij}\left(v_i^2 - v_i v_j\, cos(\delta_{ij})\right) - B_{ij} v_i v_j sin(\delta_{ij})) = 0 \tag{7}$$

$$\sum_{i\in G_n} q_g^i - \sum_{i\in D_n} [(q_{dPT}^{i,max} - q_{dSH}^{i}) + (q_{dCR}^{i,max} - q_{dCR}^{i}) + q_{dDR}^{i}] - \sum_{j\in N_b} [B_{ij}\left(v_i^2 - v_i v_j\, cos(\delta_{ij})\right) - G_{ij} v_i v_j sin(\delta_{ij})) = 0 \tag{8}$$

$$[G_{ij}\left(v_i^2 - v_i v_j\, cos(\delta_{ij})\right) - B_{ij} v_i v_j sin(\delta_{ij})]^2 +[- B_{ij}\left(v_i^2 - v_i v_j\, cos(\delta_{ij})\right) - G_{ij} v_i v_j sin(\delta_{ij})]^2 \le S_{ij}^{max^2} \tag{9}$$

$$0 \le P_{dDR}^{i} \le P_{dDR}^{i,max} \tag{10}$$

$$0 \le P_{dCR}^{i} \le P_{dCR}^{i,max} \tag{11}$$

$$0 \le P_{dSH}^{i} \le P_{dSH}^{i,max} \tag{12}$$

$$q_{dPT}^{i} = tg\varphi_i p_{dPT}^{i} \tag{13}$$

$$q_{dDR}^{i} = tg\varphi_i p_{dDR}^{i} \tag{14}$$

$$q_{dCR}^{i} = tg\varphi_i p_{dCR}^{i} \tag{15}$$

$$q_{dSH}^{i} = tg\varphi_i p_{dSH}^{i} \tag{16}$$

$$q_g^{i,min} \le p_g^i \le p_g^{i,max} \tag{17}$$

$$q_g^{i,min} \le q_g^i \le q_g^{i,max} \tag{18}$$

$$v^{min} \le v_i \le v^{max} \tag{19}$$

$$-2\pi \le \delta_i \le 2\pi \tag{20}$$

Equations 7 and 8 show the power balance constraint in each bus; Equation 9 denotes the limit of power passing each lines; Equations 10-12 demonstrate the maximum values of the price-responsive part, DB-participating part and demand cut-off. Equations 13-16 demonstrate the fixed nature of the load power coefficient, Equations 17 and 18 show the minimum and maximum generation, and Equations 19 and 20 show the limits of bus voltage size and angle.

3. Programming objectives

The main goal of TEP is to provide a competitive, equitable and reliable environment for all at the lowest costs. Therefore, objectives must be defined such that the competition demonstrates the reliability level and investment costs. The following objectives were pursued here.

3.1.Investment cost

In both traditional and electricity market settings, a design's economic nature is a priority for its selection. Therefore, investment cost must be regarded as an economic criterion in expansion planning to minimize expansion costs. As the programming is dynamic, the total investment cost is calculated by including the capital discount rate as:

$$ic^t = \sum\nolimits_{l=\Omega} (ic_l u_l^t) + \sum\nolimits_{g=\Omega} (ic_g u_g^t) \tag{21}$$

$$IC^{PV} = \sum_{t=1}^{N_y} \frac{ic^t}{(1+d)^{t-1}} \tag{22}$$

where ic^t is the investment cost in the tth year; ic_g and ic_l are respectively the installation costs of generators and transmission line; u_g^t and ult are binary variables denoting the installation status of the generator and lines, respectively; if it is 1, it shows the installation of the device in year t of the design horizon. Ω is the set of all elements which were candidates of installations; ICPV is the total investment cost: based on the current value; d is the capital value discount percentage and NY is the number of design years.

3.2. Congestion cost

The main goal of the electricity market is to create a competitive and equitable environment for all the players. Less line congestion enables producers and consumers to have free access to all parts of the market. In other words, a sufficient transmission capacity helps increase social welfare, improve competition and balance market power. Thus, line congestion has been included as an appropriate criterion for this purpose in the electricity market. By implementing the DC load dispatch by ISO, LMPs are determined. The LMP index is calculated as a Lagrangian coefficient of the active power balance equation in each bus. For a given point of operation, the peak load of the line congestion costs is calculated from the following equation:

$$CC' = \sum_{l=\varphi} f_{l,mn}^{t}(lmp_m^t - lmp_n^t) \tag{23}$$

$$CC^{pv} = \sum_{t=1}^{N_y} \frac{cc^t}{(1+d)^{t-1}} \tag{24}$$

where cc^t is the hourly price of line congestion n year t; lmp_m^t is the LMP for bus m in year t and CC^{pv} is the total cost of line congestion based on the current value.

3.3. Load outage cost

In emergencies, a good network configuration can help prevent load outage. Presenting a reliable network under system events is a goal of TEP. This paper adopts the NERC definition of security (single-event or N-1 security). The total expected load outage costs in the normal conditions and events are assumed as the criterion for reliability and the third objective:

$$minf_3 = LCC_0 + LCC_1 \tag{25}$$

$$LCC_0 = \sum_{N_y=1}^{5} \sum_{i \in N_b} p_{dSH}^{i} VOLL_{dSH}^{i} \tag{26}$$

$$LCC_1 = \sum_{N_y=1}^{5} \sum_{mn \in \psi} \sum_{i \in N_b} p_{dSH}^{i} VOLL_{dSH}^{i} \tag{27}$$

This formulation can be easily changed for mixing the event probabilities. Although events can be selected by an appropriate method to limit the time of calculations in the large-scale transmission planning, in the proposed case study, all the events re used. This formulation has two advantages: First, the optimization problem will become feasible at all times due to the presence of load outage; second, defining the reliability criteria as an objective will allow the decision-maker to perform a cost-benefit analysis.

4. Metaheuristic algorithm

Hybrid optimization problems are often expressed with ease, but solved with difficulty. There are two categories of algorithms for solving hybrid problems: exact and approximation.

The exact algorithm ensures finding the best solution. The problem is that these algorithms are not efficient for hard problems; the solution time will exponentially rise for hard problems; and the exact solution will not be satisfactory for most of the NP-hard problems.

If the optimal solution cannot be found by an exact algorithm in practice, we must use approximation algorithms. These algorithms, also known as heuristic algorithms, look for the proper and near-optimal solutions. This method reduces the computational time compared to the previous method, but there is no guarantee for presenting the best solution.

Metaheuristic algorithm:

There are certain disadvantages to heuristic algorithms. Heuristic algorithms guarantee either very few solutions (i.e., one algorithm cannot be used for other problems), or stop in a weak and unreliable local optimum due to the existence of improved iteration methods. Metaheuristic algorithms have been proposed to resolve these problems. This method which was introduced in the 1980s can be used to solve problems with hard optimization.

Definition of metaheuristic algorithms:

Metaheuristic algorithms are a set of algorithms applied to heuristic algorithms and release them from local optima while allowing for the use of heuristic algorithms in a large number of problems. We mentioned two problems of local optima and limited solutions for heuristic algorithms; these two problems are resolved using metaheuristic algorithms.

In a similar definition, metaheuristic is a general algorithmic framework that can present solutions specific to a new problem with few changes (contrary to heuristic algorithms that are unique to a certain problem).

Some algorithms in this category are inspired by nature. Some algorithms have a memory, i.e., they use the results obtained when running the algorithm.

Examples of metaheuristic algorithms include the GA, ant colony, bee colony, refrigeration simulation, tabu search, salp swarm, etc.

4.1. Multi-objective salt swarm algorithm (MSSA)

The MSSA was proposed by Mirjalili et al. based on the social behavior of salp. Salps belong to the Salpidae family and have a transparent and cylindrical body. Their body tissue resembles that of jellyfish and they move similarly. Their body pumps water to provide a thrust force forward. The following image shows a salp [33].

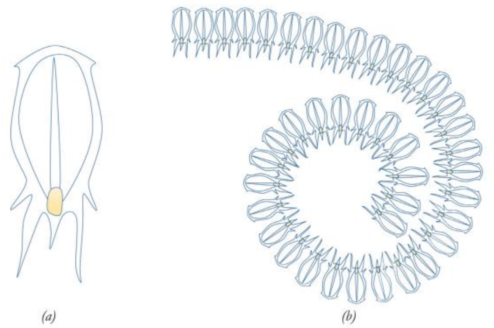

Fig 1. A) a salp, B) a group of salps

In modeling the salp swarm algorithm, their social and chain-like behavior is used for better motility by using rapid coordinated movement in chasing food. In the mathematical modeling of salp chains, the population is first divided into two groups of the leader and followers. The leader is the salp at the front of the chain, while the other salps are the followers. The leader is in charge of leading the group, while the followers follow each other. Similar to other population-based methods, the salp's position is defined in an n-dimensional search space, in which n is the number of variables of a certain problem. Therefore, the position of all salps is stored in a 2D matrix, known as x. It is also assumed that there is a food source F in the search space as the goal of the swarm. The following equation is used to update the leader's position:

$$x_j^i = \begin{cases} F_j + c_1\left(\left(ub_j - lb_j\right)c_2 + lb_j\right) & c_3 \geq 0 \\ F_j - c_1\left(\left(ub_j - lb_j\right)c_2 + lb_j\right) & c_3 \leq 0 \end{cases} \tag{28}$$

where x_j^i indicates the position of the first salp (leader) in the Jth dimension; Fj is the position of the food source in the Jth dimension; ubj shows the upper bound of the jth dimension; lbj shows the lower bound of the jth dimension and c1, c2 and c3 are random numbers. This equation shows that the leader only updates its position compared to the food source. The c1 coefficient is the most important parameter in the SSA because it balances the discovery and use of the definition as follows:

$$C_1 = 2e^{-(\frac{4l}{L})^2} \tag{29}$$

Here, I is the current iteration and L the maximum number of iterations. Parameters c2 and c3 are random numbers uniformly generated in the [0,1] interval. They show whether the next position in the jth dimension must be towards positive or negative infinity and they also specify the step size. The position of the followers is updated via the following equation (Newton's law of motion):

$$x_j^i = \frac{1}{2}at^2 + v_0 t \tag{30}$$

$$a = \frac{v_{final}}{v_0} \tag{31}$$

$$v = \frac{x - x_0}{t} \tag{32}$$

Where $i \geq 2$ and x_j^i indicate the position of the ith follower salp in the jth dimension, T is time and V0 is the primary velocity.

Since time in optimization is iteration, the difference between teh iterations is 1. By considering V0 = 0, this equation can be rewritten as:

$$x_j^i = \frac{1}{2}(x_j^i + x_j^{i-1}) \tag{33}$$

Where $i \geq 2$ and x_j^i indicate the position of the ith follower salp in the jth dimension. To solve a multi-objective problem, a set of solutions known as the optimal Pareto set is used. The SSA can move the salps towards the food source and update them during iterations. Still, this algorithm cannot solve multi-objective problems due to two reasons:

1) The SSA saves only one solution as the best solution; therefore, it cannot store several solutions as the best solutions for a multi-objective problem.

2) The SSA updates the food source with the best solution obtained so far in each iteration, but there is no single appropriate solution to multi-objective problems.

The first problem can be resolved by equipping the SSA with a good source archive. This archive stores the best non-dominated solutions obtained so far during the optimization and is very similar to the MOPSO archive. This archive has maximum size to store a limited number of non-dominated solutions. During optimization, by using Pareto dominated operators, each salp is compared to all the residents of the archive. If a salp dominates a solution in the archive, it replaces the solution. If a salp dominates a set of solutions in the archive, they must all be eliminated and the salp is added to the archive. If at least one of the residents of the archive dominates a salp in the next population, it must be quickly released. If a salp does not dominate the residents of the archive, it must be added to the archive. These results can ensure that the archive always stores non-dominated solutions obtained so far by the algorithm. Still, there is a certain case, in which the archive is full, and a salp does not dominate the residents.

The simplest solution is to randomly delete a resident and replace it with a non-dominated salt. A more reasonable approach is to eliminate a similar non-dominated solution in the archive. A comparative multi-objective algorithm must be able to find optimal Pareto solutions with a uniform distribution. As such, the best candidate for deletion from the archive is one that is located in a populous area. This method improves the distribution of residents in the archive during iterations. To find non-dominated solutions with a populous neighborhood, the number of neighborhood solutions is enumerated with specific maximum distance and is assumed.

This distance is defined as the difference between two maximum and minimum vectors based on the total number, where the values of the two vectors aim to store the maximum and minimum values of each objective. The archive holds a solution in each part of the best case. After allocating one order to each resident based on the number of neighborhood solutions, a roulette is used to select one of them. The higher the number of neighborhood solutions for a solution, the higher the probability of its deletion from the archive would be.

4.2. Fuzzy satisfaction method

After obtaining a set of solutions in the first Pareto front, it is essential to use a proper secondary method to select the best planning design. Power system designers pursue different objectives and have different tastes as to the importance of each expansion design owner; therefore, to determine the satisfaction level related to each programming criterion, the fuzzy satisfaction method can be very beneficial in solving problems with multiple objective functions due to its simplicity and similarity to human judgment in decision-making. Each design is assigned fuzzy sets by equations known as membership functions. The membership function is specified as a descending uniform function with upper and lower limits. Based on the membership functions shown below, each solution is assigned a fuzzy value as follows:

$$\mu_{f_x} = \begin{cases} 0 & f_i(x) > f_i^{max} \\ \dfrac{f_i^{max} - \ f_i(x)}{f_i^{max} - f_i^{min}} & f_i^{min} \le f_i(x) \le f_i^{max} \\ 1 & f_i \le f_i^{min} \end{cases} \tag{34}$$

Where x is the index of each optimal design of the Pareto front;

$f_i(x)$ ... is the ith objective function belonging to design x; μ_{f_x} ... is the objective function of each design belonging to the ith criterion; and f_i^{max} and f_i^{min} are the minimum and maximum values of the ith criterion. Naturally, the closer the design to the minimum value, the closer the fuzzy value to 1, and vice versa.

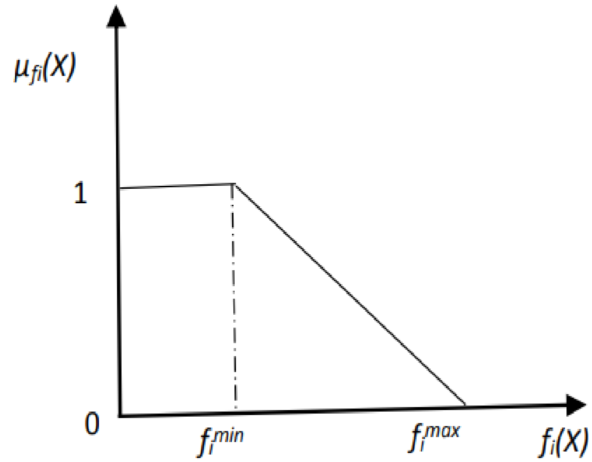

Fig 2. Membership function for programming criteria

5. Case study

The proposed TEP algorithm is applied to the IEEE 24-bus test grid shown below and implemented in MATLAB. The network data for this system can be found in [34]. It is assumed that the system should be expanded for future conditions by increasing the generation and load demand by 1.61 times of its original values, i.e., load level of 4590 MW and generation level of 5480 MW. These conditions belong to a 10% annual load increase rate with a five-year planning horizon. It is also assumed that the candidate branches can be constructed in all 34 existing paths, plus 10 new paths, the data of which are given in the appendix. The parameters of new lines in the existing paths are the same as the parameters of the existing lines. Due to environmental requirements, up to three branches can be installed in the existing and new paths and up to four power transformers in the substations. Herein, only the wholesale electricity market is foreseen. The value of $VOLL_{SH}$ is equal to 1000$\$/MWh$and $VOLL_{CR}$ 50$\$/MWh$and.

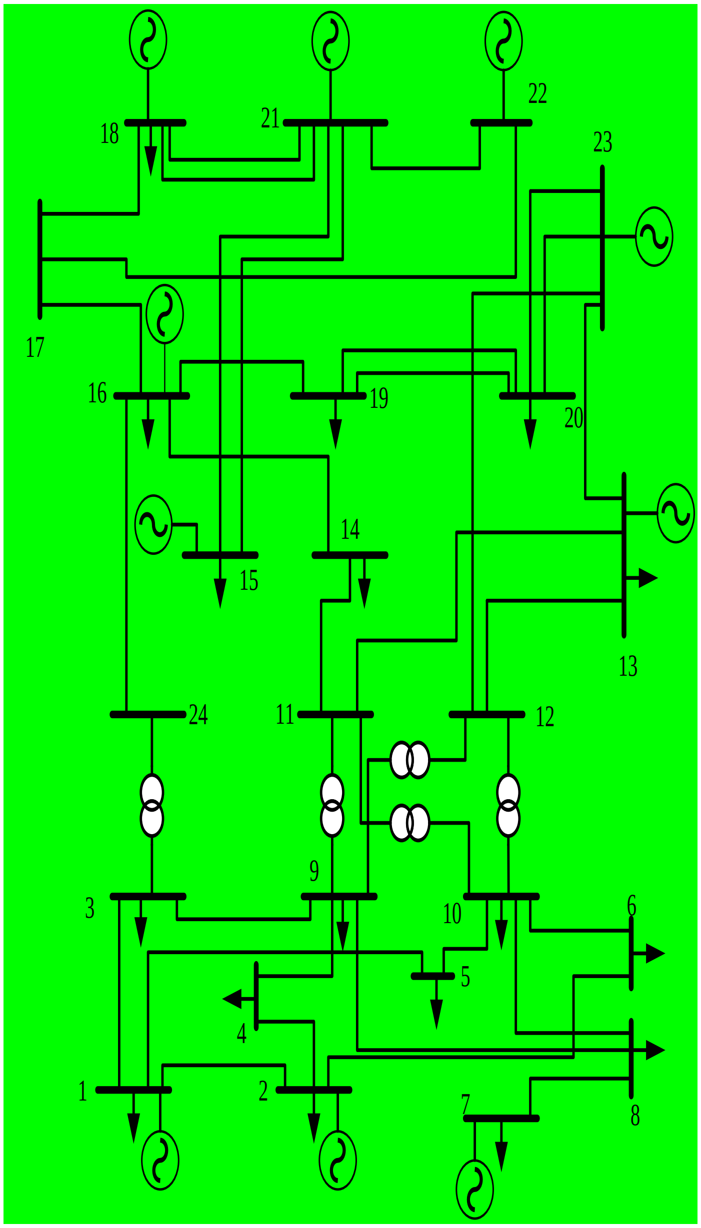

Fig 3. Test IEEE 24-bus system

For these conditions, by using the proposed algorithm with the population size of 200 and after 50 iterations, 41 non-dominated solutions are found in the presence of 89 DR sources and without them. Figure 4 illustrates these non-dominated solutions. Due to the difficulty of depiction in a 3D space, two 2D vectors are used. Note that solutions that look dominated in each figure are, in fact, non-dominated by considering the third objective not shown in the figure. Fig 4a shows the reduction in congestion cost by increasing the investment, as well as less investment in the presence of DR sources. The least investment for completely removing the congestion is 121 M$ in the presence of DR sources and 137 M$ without DR sources.

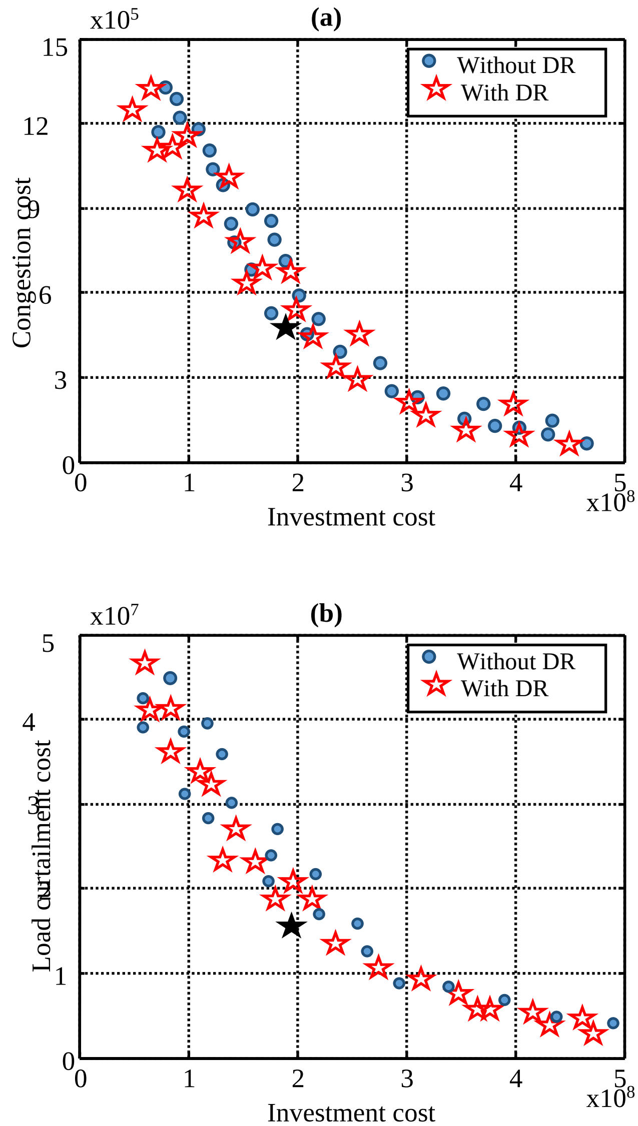

Fig 4. Distribution of Pareto solutions, a) congestion cost compared to investment, b) load cut-off cost per investment

In finding the optimal design, based on Table 1, we examine two states with different values of satisfactory levels. The satisfactory level for the first objective (investment cost) is higher in the first state than the second one. In other words, in the first state, the decision-maker is inclined to less cost, while in the second state, higher costs are permissible. Tables 2 and 3 list the optimal design in two states of satisfactory levels for the presence and absence of DR sources. Based on Table 2, it is observed that without DR sources, the congestion cost severely rises. In

Table 3 without Dr sources, the investment and load cut-off costs are increased.

Table 1. Satisfactory levels for the two states

μ_{r3}	μ_{r2}	μ_{r1}	**Satisfactory level**
0.7	0.7	0.7	Model 1
0.7	0.7	0.5	Model 2

Table 2. Characteristics of the optimal design for the first state

LCC (*10^7$/h)	**TCS** (*10^4$/h)	**IC** (M$)	**Model 1**
0.04	0.48	185.3	With DR sources
0.14	0.00095	213.2	Without DR sources

Table 3 presents the optimal value of acceptance of bids made by players participating in the DB program as a percentage per maximum permissible value for the first state. In this case, almost the maximum capacity of buses 1 to 10 is used. These buses are optimal options for DR investors.

Table 3. Optimal DB participation percentage in the first-case optimal design

Y_5	Y_4	Y_3	Y_2	Y_1	Year Bus
100%	100%	100%	100%	67.6%	1
100%	100%	90%	100%	80%	2
100%	100%	100%	100%	100%	3
90%	100%	100%	100%	100%	4
100%	100%	100%	100%	100%	5
100%	100%	100%	100%	100%	6
100%	100%	100%	100%	20%	7
39%	100%	65%	100%	80%	8
100%	100%	100%	100%	100%	9
100%	100%	100%	100%	100%	10

Table 4 shows the value of cut-off load for the first-case optimal design as a percentage per maximum permissible value. Evidently, in the presence of DR sources, load supply in bus 6 has faced problems and, every year, a percentage of load is forced to cut off. Thus, bus 6 is among the main candidates for further DR expansion or power station installation. Without DR, buses 5 and 6 face problems in the fifth year. Note that in this state, the congestion cost is very high. In the second state, by increasing the investment, the DB participation and cut-off load are reduced to 0 in the presence and absence of DR sources.

Table 4. Percentage of cut-off load for the optimal first-state design

Y_5	Y_4	Y_3	Y_2	Y_1	Year Bus	
28.7 %	12.8 %	18.3 %	39.2 %	21 %	8	With DR
31%	0%	0%	0%	0%	7	Without DR
18.2 %	0%	0%	0%	0%	5	

6. Conclusion

In this paper, a dynamic multi-objective TEP was performed under reliability constraints in the market setting based on the DB DR program and price-dependent bids. These programs directly participated in the market clearing process and their impacts on the TEP were examined. Investment, congestion and load cut-off costs were selected as the objectives. The salp optimization algorithm, along with the AC network model, was proposed for the dynamic multi-objective programming. This method was implemented on a test IEEE 24-bus system in a five-year horizon with and without DR sources. Then, the optimal designs were selected from non-dominated solutions via the fuzzy satisfactory method with different levels. It was observed that at a higher level of satisfaction for the first objective, i.e., investment cost, the use of DR sources severely reduces congestion costs and, thus, helps create a more competitive electricity market. By decreasing the satisfaction level for the investment cost, the use of DR sources decreased the investment cost and load cut-off. In each case, the optimal value required for DB participation in each year was obtained for each bus to specify optimal buses for DR investors.

Appendices

The line characteristics for new paths are given in Table 6. The cost function for each GENCO is defined as $.a_g^i p_g^{i2} + b_g^i p_g^i + c_g^i$

Table 5. Line characteristics

Investment cost (10^6$)	**Reactance** (p.u.)	**Resistance** (p.u.)	**Capacity** (MW)	**To**	**From**

35	0.1344	0.0348	175	8	1
25	0.1267	0.0328	175	7	2
33	0.125	0.032	175	8	2
50	0.192	0.0497	175	7	6
18	0.19	0.049	175	8	6
62	0.0447	0.0057	175	14	13
86	0.0620	0.0080	175	23	14
114	0.0822	0.0105	175	23	16
84	0.0606	0.0078	175	23	19
36	0.055	0.007	175	23	20

REFERENCES

[1] Solat S, Aminifar F, Shayanfar H. Changing the regulations for regulating the changes: From distribution system operator (DSO) to electricity distribution stakeholders' organization (EDSO). Energy & Environment 2022:0958305X211073800.

[2] Oskouei MZ, Şeker AA, Tunçel S, Demirbaş E, Gözel T, Hocaoğlu MH, et al. A Critical Review on the Impacts of Energy Storage Systems and Demand-Side Management Strategies in the Economic Operation of Renewable-Based Distribution Network. Sustainability 2022; 14:2110.

[3] Ameli K, Aghaebrahimi MR, Falaghi H. Dynamic Transmission Expansion Planning in Re-structured Power Systems considering Demand Response. Iranian Electric Industry Journal of Quality and Productivity 2018; 6:56–66.

[4] Baecker BR, Candas S. Co-optimizing transmission and active distribution grids to assess demand-side flexibilities of a carbon-neutral German energy system. Renewable and Sustainable Energy Reviews 2022; 163:112422.

[5] Dashtdar M, Flah A, Hosseinimoghadam SMS, Kotb H, Jasińska E, Gono R, et al. Optimal Operation of Microgrids with Demand-Side Management Based on a Combination of Genetic Algorithm and Artificial Bee Colony. Sustainability 2022; 14:6759.

[6] Shayanfar HA, Ghasemi A, Amjady N, Abedinia O. Optimal sizing and placement of distribution generation using imperialist competitive algorithm. Proceedings on the International Conference on Artificial Intelligence (ICAI), The Steering Committee of The World Congress in Computer Science, Computer …; 2012, p. 1.

[7] Roldán C, de la Nieta AAS, García-Bertrand R, Mínguez R. Robust dynamic transmission and renewable generation expansion planning: walking towards sustainable systems. International Journal of Electrical Power & Energy Systems 2018; 96:52–63.

[8] Gomes PV, Saraiva JT. State-of-the-art of transmission expansion planning: A survey from restructuring to renewable and distributed electricity markets. International Journal of Electrical Power & Energy Systems 2019; 111:411–24.

[9] Fathtabar H, Barforoushi T, Shahabi M. Dynamic long-term expansion planning of generation resources and electric transmission network in multi-carrier energy systems. International Journal of Electrical Power & Energy Systems 2018; 102:97–109.

[10] Saber H, Moeini-Aghtaie M, Ehsan M. Developing a multi-objective framework for expansion planning studies of distributed energy storage systems (DESSs). Energy 2018; 157:1079–89.

[11] Saber H, Moeini-Aghtaie M, Ehsan M. Developing a multi-objective framework for expansion planning studies of distributed energy storage systems (DESSs). Energy 2018; 157:1079–89.

[12] Babatunde OM, Munda JL, Hamam Y. A comprehensive state-of-the-art survey on power generation expansion planning with intermittent renewable energy source and energy storage. International Journal of Energy Research 2019; 43:6078–107.

[13] Kazemi M, Ansari MR. An integrated transmission expansion planning and battery storage systems placement-A security and reliability perspective. International Journal of Electrical Power & Energy Systems 2022; 134:107329.

[14] Li C, Conejo AJ, Liu P, Omell BP, Siirola JD, Grossmann IE. Mixed-integer linear programming models and algorithms for generation and transmission expansion planning of power systems. European Journal of Operational Research 2022; 297:1071–82.

[15] Gjorgiev B, David AE, Sansavini G. Cascade-risk-informed transmission expansion planning of AC electric power systems. Electric Power Systems Research 2022; 204:107685.

[16] Jadidoleslam M, Bijami A, Ebrahimi A. Generation expansion planning by a modified SFL algorithm. Computational Intelligence in Electrical Engineering 2011; 2:27–44.

[17] Meza JLC, Yildirim MB, Masud ASM. A model for the multiperiod multiobjective power generation expansion problem. IEEE Transactions on Power Systems 2007; 22:871–8.

[18] Foroud AA, Abdoos AA, Keypour R, Amirahmadi M. A multi-objective framework for dynamic transmission expansion planning in competitive electricity market. International Journal of Electrical Power & Energy Systems 2010; 32:861–

72.
[19] Buygi MO, Balzer G, Shanechi HM, Shahidehpour M. Market-based transmission expansion planning. IEEE Transactions on Power Systems 2004; 19:2060–7.
[20] Tor OB, Guven AN, Shahidehpour M. Congestion-driven transmission planning considering the impact of generator expansion. IEEE Transactions on Power Systems 2008; 23:781–9.
[21] Arasteh H, Sepasian MS, Vahidinasab V. Incorporation of distribution system reconfiguration and expansion planning problems by considering the role of demand response resources. Journal Of Electrical Systems and Signals 2015; 3:23–36.
[22] Mazhari SM, Bagher A, Monsef H, Lesani H. A New Approach for Transmission Network Expansion Planning Considering Actual Worth of Adequacy Using Modified Artificial Bee Colony Algorithm. Computational Intelligence in Electrical Engineering 2012; 2:1–20.
[23] Sharan I, Balasubramanian R. Integrated generation and transmission expansion planning including power and fuel transportation constraints. Energy Policy 2012; 43:275–84.
[24] Jenabi M, Ghomi SMTF, Smeers Y. Bi-level game approaches for coordination of generation and transmission expansion planning within a market environment. IEEE Transactions on Power Systems 2013; 28:2639–50.
[25] Makholm JD. The renewable energy supply chain problem: A new geography of power supply and new species of electricity transmission. The Electricity Journal 2022; 35:107079.
[26] Ma M, Huang H, Song X, Peña-Mora F, Zhang Z, Chen J. Optimal sizing and operations of shared energy storage systems in distribution networks: A bi-level programming approach. Applied Energy 2022; 307:118170.
[27] Celli G, Pilo F, Pisano G, Ruggeri S, Soma GG. Risk-oriented planning for flexibility-based distribution system development. Sustainable Energy, Grids and Networks 2022;30:100594.
[28] Liu J, Tang Z, Zeng PP, Li Y, Wu Q. Fully Distributed Second-Order Cone Programming Model for Expansion in Transmission and Distribution Networks. IEEE Systems Journal 2022.
[29] Golombek R, Lind A, Ringkjøb H-K, Seljom P. The role of transmission and energy storage in European decarbonization towards 2050. Energy 2022; 239:122159.
[30] Kazemi M, Ansari MR. An integrated transmission expansion planning and battery storage systems placement-A security and reliability perspective. International Journal of Electrical Power & Energy Systems 2022; 134:107329.
[31] Botterud A, Ilic MD, Wangensteen I. Optimal investments in power generation under centralized and decentralized decision making. IEEE Transactions on Power Systems 2005; 20:254–63.
[32] Singh K, Padhy NP, Sharma J. Influence of price responsive demand shifting bidding on congestion and LMP in pool-based day-ahead electricity markets. IEEE Transactions on Power Systems 2010; 26:886–96.
[33] Mirjalili S, Gandomi AH, Mirjalili SZ, Saremi S, Faris H, Mirjalili SM. Salp Swarm Algorithm: A bio-inspired optimizer for engineering design problems. Advances in Engineering Software 2017; 114:163–91.
[34] Botterud A, Ilic MD, Wangensteen I. Optimal investments in power generation under centralized and decentralized decision making. IEEE Transactions on Power Systems 2005; 20:254–63.