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A Reliable Approach for Solving Transmission Network Expansion Planning with Objective of Planning Cost Reduction

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Highlights

- Introduction of a multi-objective optimization framework for transmission expansion planning using AC optimal power flow.
- Fitness function incorporates investment costs, expected operation costs, and cost of load curtailment.
- > Formulation of optimization problem as large-scale non-convex mixed integer nonlinear programming problem.
- Application of particle swarm optimization algorithm to search for optimal planning solutions.
- Illustration of proposed method's performance using scenarios of fixed load and generation, fixed load and variable generation, and variable load and generation on IEEE 30-bus test system.

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Abstract

This article presents a multi-objective optimization framework for transmission expansion planning using AC optimal power flow to identify the most suitable set of projects and their scheduling along the planning horizon. The candidate plans are evaluated using a fitness function that considered objective function for transmission expansion planning problem is composed of two terms. The first term is related to the sum of investment costs which is the construction cost of new lines; the second term is related to the expected operation costs, which is the expected cost of generation in the power system. The third term is related to the cost of load curtailment. The optimization problem represented in this paper is a large-scale non-convex mixed integer nonlinear programming problem with multiple local minima. The transmission expansion planning procedure is formulated as an optimization problem to overcome the difficulties in solving the nonconvex and mixed-integer nature of the optimization problems. The particle swarm optimization algorithm searches for optimal planning to reach the fitness requirement. transmission expansion planning problem involves a decision on the location and number of new transmission lines. In optimization process all constrains are modeled beside problem which should be considered in investment. The proposed transmission expansion planning model has been applied to the wellknown IEEE 30-bus test system. In order to illustrated the performance of the proposed method, we consider three scenarios as fix load and generation, fixed load and variable generation and variable load and generation. The detailed results of the case study are presented and thoroughly analyzed. The obtained transmission expansion planning results show the efficiency of the proposed algorithm.

Nomenclature

Indices		G_{ij}	Conductance of line ij
AC-OPF	AC optimal power flow	γ	Price factor
CLC	Cost of load curtailment	INVC	Investment cost
EOC	Expected operation costs	L_i	Length of ith line
IC	Investment costs	λ	Energy marginal section in reference bus
IPM	Interior Point Method	OPC	Operation cost

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OPF	Optimal Power Flow	P_{gen}	Active generation power
PSO	Particle swarm optimization	P_{load}	Load active power
RPP	Reactive power planning	Q_{load}	Demand Reactive power
TEP	Transmission expansion planning	Q_{gen}	Generator Reactive Power
Parameters and variables		S_{ji}^{max}	Maximum mixed power limit
a_c^j	Constant operation Price factor	TP	Time of study horizon
a_{v}^{j}	Variable operation Price factor	V_i	Voltage of ith bus
B_{ij}	Susceptance of line ij	V_i^{max}	Upper limit of voltage at bus i
δ_i	Angle of voltage of ith bus	V_i^{min}	Lower limit of voltage at bus i

1. Introduction

Due to growing electricity consumption in the power system, new power lines in the transmission system are necessary to provide alternative paths to power transfer for future demand from generation. Using the Transmission Expansion Planning (TEP), these new lines that should be placed in the electrical power system are determined. Minimizing the investment costs of new lines is the main goal of TEP problems. In addition, in this minimizing process, the operational constraints should be considered. In deregulated power systems, nondiscriminatory and competitive environment providing is considered in the goal of TEP problem too.

The first suitable transmission planning scheme is considered in the TEP problem, such as other planning problems. In the next step, this considered formulation written as an optimization problem. Finally, by applying the appropriate optimization technique, the best planning is achieved. In previous studies, both mathematical and heuristic optimization methods are applied for TEP problems. In order to run the optimization technique, the system's power Current should be done in each optimization step. Both of DC and AC power current models can be considered. Having an AC model is completer than the DC model, but this does not mean that DC models are always incorrect.

The literature on this topic includes many publications that can be gathered in two large groups. On one side, there are applications designed to analyze pre-prepared expansion plans. Most of these formulations correspond to software packages developed by utilities or by research centers related to them. Packages as TRELSS and CREAM developed by EPRI and several others implemented by CEPEL in Brazil, ENEL in Italy, and EDF in France are examples of these approaches. On the other hand, there are optimization models designed to build expansion plans according to some criteria. The number of publications on this topic is very large [1], and all researchers do not adopt common and general transmission expansion formulation. Traditionally, the expansion formulations included continuous variables to represent the capacity of new branches, thus requiring approximations to obtain a final technically feasible solution. For instance, Refs [2], [3]. describe linear and non-linear approaches to the TEP

problem. Some other papers, as [4], [5], describe mixedinteger formulations and adopt, for instance, Branch & Bound and Benders Decomposition based methods in a way to preserve the discrete nature of investments. Some others select investments according to a Merit Index or a trade-off relation between the investment cost and the resulting benefit [6], [7]. More recently, several emergent techniques as simulated annealing, genetic algorithms, Tabu search, and the game theory started to be applied to this problem. Ref [8]. describe the application of the harmony search algorithm to the transmission expansion problem, [9] details the use of Tabu Search [10], adopts simulated annealing,[11] and uses Grasp. Finally, ref. [12] describes a multi-agent implementation based on cooperative games. These authors mention the advantages of these approaches to address this complex combinatorial problem in identifying a feasible solution in a manageable computation

Many kinds of literatures have been proposed methods for TEP. Ref [4] is considered losses costs and solved the planning by mixed-integer linear programming. Integration of TEP and generation expansion planning (GEP) is addressed in [13] analyzed in southern Africa. Xiufan Ma, Ying Zhou [14] proposed a coordination planning model between the TEP and GEP considering large wind farms. Also, transmission planning cost was taken into account as a risky constraint. The comprehensive optimal expansion planning model represents the capital cost of new generation, fuel cost, and capital cost of new lines with fuel transportation constraints [15]. Daniel Delgado and João Claro [16] propose an approach considering uncertainty in TEP that can help improve the balance between different and important concerns such as network utilization, demand satisfaction, or dynamic sourcing from lower-cost generation options. Probabilistic transmission expansion planning based on Congestion management and considering roulette wheel simulation to achieve the optimal capacity of new transmission lines is investigated [17]. The simultaneous approach of the TEP integrated substation expansion planning using DC optimal power current that minimized the sum of investment costs (IC) and expected operating costs considering uncertainty in load is reported in [18]. Recently, the TEP optimization problems integrated RPP problem has been done in some

of the literature. In ref [19], an AC model of TEP problem (AC-TEP) associated with Reactive Power Planning (RPP) for minimizing investment cost and maximizing social benefit at the same time is presented. Also, the Expected Energy Not Supplied (EENS) index is limited by a constraint to improve the system's reliability. A mathematical model for solving simultaneous TEP and RPP problems (TEPRPP) via an AC model Using a combined algorithm of genetic algorithm and Interior Point Method (IPM) is proposed in [20].

This paper proposes an AC-OPF based transmission expansion planning in which binary variables are related to the candidate lines. The proposed method's objectives are to minimize the investment cost, operation cost, and cost of load curtailment related to new transmission lines along the planning horizon subjected to several constraints having technical and financial natures. The problem of the proposed TEP is formulated as a multi-objective optimization problem that represents all the years of the planning horizon. Then PSO algorithm is employed to search for optimal planning. Regarding the mixed-integer nature of the objective function, we developed a set of adaptations to the Evolutionary PSO algorithm to turn it more adequate to treat discrete problems. The paper is organized as follows: In Section 2, the proposed problem formulation is presented. The particle optimization algorithm is presented in Section 3. Illustrative tests and discussions are demonstrated in Section 4, and finally, the major contributions and conclusions are drawn in Section 5.

2. Problem Formulation

The formulation of TEP in this paper is defined as a discrete problem in which the k number of potential lines connected along j^{th} path between pairs of nodes from N nodes of the system is established. The investment decisions are incorporated through UK's binary decision variables, which take the value 1 if line k is built and 0 otherwise. In practice, these decisions can be thought of as selecting appropriate combinations of lines with different transmission capacities and technical characteristics.

The objective function (*F*) of this paper includes a sum of the investment cost (INVC), operation cost (OPC) for setting up new transmission lines, and cost of load curtailment. Mathematically the objective function is expressed as:

$$F = INVC + OPC + CLC \tag{1}$$

where investment cost, operation cost, and cost of load curtailment are defined as Esq. (2) - (4), respectively.

$$INVC = \sum_{l=1}^{N_k} IC_l \times u_l \times L_l$$
 (2)

$$OPC = \sum_{j=1}^{N_k} T_P \times 8760 \times \left(\alpha_v^j P_{line}^j + \alpha_c^j\right) \times u_l^j$$
 (3)

$$CLC = \sum_{i=1}^{N_{bus}} \alpha_i r_i \tag{4}$$

where IC_I is i^{th} line investment cost, L_i is the length of i^{th} transmission line, T_P is study horizon, ρ_t^N is the price of power in horizon N and time t, α_v^j and α_c^j are variable and constant operation cost coefficients, respectively, and u_l is a binary variable.

The constraints of TEP problem can be described by Eqs. (5) - (16). Constraints (5) and (6) are active and reactive power balance constraints at every node. Eqs (7), (8) indicate the active power currents from existing and candidate lines, respectively. The reactive power currents of lines are given in (8). The constraint of binary variables is given by (9), which shows that the summation of binary variables is equal to building lines. The transmission capacity constraints for lines are defined as (13) for the real power injection and (14) for the reactive power injection in the lines, respectively. The losses of existing and candidate lines are limited by (15). Voltage limits are given by (16).

$$P_{gen}^{i} - P_{load}^{i}(1 - r_i) = \sum_{j \in bus_i} P_{Line}^{j}$$
(5)

$$Q_{gen}^{i} - Q_{load}^{i}(1 - r_{i}) = \sum_{j \in bus_{i}}^{j \in bus_{i}} Q_{Line}^{j}$$

$$\tag{6}$$

$$P_{Line}^{ij} = |V_i|^2 G_{Line}^{ij} -|V_i||V_i| \times (G_{Line}^{ij} \cos(\theta_i - \theta_i) + B_{Line}^{ij} \sin(\theta_i - \theta_i))$$
(7)

$$P_{Line}^{ij} = |V_{i}|^{2} G_{Line}^{ij}$$

$$-|V_{i}||V_{j}| \times \left(G_{Line}^{ij} \cos(\theta_{i} - \theta_{j}) + B_{Line}^{ij} \sin(\theta_{i} - \theta_{j})\right)$$

$$Q_{Line}^{ij} = -|V_{i}|^{2} B_{Line}^{ij}$$

$$-|V_{i}||V_{j}| \times \left(G_{Line}^{ij} \sin(\theta_{i} - \theta_{j}) - B_{Line}^{ij} \cos(\theta_{i} - \theta_{j})\right)$$

$$\sum_{t=1}^{T_{p}} u_{lt} = N l$$
(9)

$$\sum_{l=1}^{N} u_{lt} = N l \tag{9}$$

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

$$Q_{gen}^{i,\min} \le Q_{ex,Line}^{i} \le Q_{gen}^{i,\max} \tag{11}$$

$$0 \le r_i \le P_{Load}^i \tag{12}$$

$$P_{Line}^{i,\min} \le P_{Line}^{i} \le P_{Line}^{i,\max} \tag{13}$$

$$Q_{Line}^{i,\min} \le Q_{Line}^{i} \le Q_{Line}^{i,\max} \tag{14}$$

$$P_{loss}^{i,\min} \le P_{loss}^{i} \le P_{loss}^{i,\max} \tag{15}$$

$$\left|V_i^{\min}\right| \le \left|V_i\right| \le \left|V_i^{\max}\right| \tag{16}$$

3. Particle swarm optimization algorithm

PSO was introduced by Kennedy and Eberhart (1995) as a result of motivation by the behavior of bird flocking, insect swarming, and fish schooling. It consists of several individuals (particles) refining their position in a given search space. Each particle is characterized by its position and represents a candidate solution to the problem at hand. The particles change their positions in a multi-dimensional search space to explore higher fitness positions. PSO starts with an initial random population of particles where each particle is a candidate solution. The particles' velocity and position are initialized at random. Each particle memorizes its own best position encountered so far during the optimization process, which is called the local best. On the other hand, the population memorizes the best position among all individual best positions obtained so far, the global best. Inertia weight is introduced to balance the particle's global and local exploration capabilities. The inertia weight is linearly decreased through optimization to emphasize the search globally at initial iterations and locally at final iterations. PSO has several advantages over other optimization techniques, including simple concepts, easy implementation, and computationally efficient. The PSO algorithm can be described in the following steps:

1. Initialization: Initialize randomly n position vectors $\{X_k(0), k=1,2,...,n\}$ each size m (depending on the problem to be solved). The elements of X_k are uniformly distributed in a suitable range. Subsequently, initialize randomly n velocity vectors $\{V_k(0), k=1,2,...,n\}$ with elements uniformly distributed between a minimum and a maximum values. The fitness of each particle is evaluated using an objective function. Initialize the local best of each particle to its initial position and the global best to the best fitness among the best locals. Finally, initialize the range of the inertia weights w (o).

2. *Update velocity*: Each element j of the velocity vector of the kth particle can be updated as follows:

$$v_{k,j}(t) = w(t)v_{k,j}(t-1) + c_1 r_1 \left(x_{k,j}^L(t-1) - x_{k,j}(t-1) \right) + c_2 r_2 \left(x_{k,j}^G(t-1) - x_{k,j}(t-1) \right)$$

$$(17)$$

where t is the iteration number, c_1 is a positive constant called the cognitive parameter and controls the step towards the particle's local best position. c_2 is a positive constant called the social parameter, and it controls the step size towards the global best position found by the entire swarm. r_1 and r_2 are uniformly distributed random

numbers in [0, 1] to add randomness to the velocity updates, $x_{k,j}(t)$ represents the current position of the particle, $x_{k,j}^L(t)$ is the particle's best position, and $x_{k,j}^G(t)$ is the global best position, w(t) is the inertia weight to control the acceleration of the particle in its original direction. Lower values of w speed up the convergence to the optima, and higher values of w encourage exploration of the entire search space. The first term of the velocity update $(w(t)v_{k,i}(t-1))$ is the inertia component to keep the particle moving in the same direction as in the previous iteration. The second term $c_1 r_1 \left(x_{k,j}^L(t-1) - x_{k,j}(t-1) \right)$ is called the cognitive component and acts as a memory of the particle, causing it to return to its local best that it has encountered so far. The third term $c_2 r_2 \left(x_{k,i}^G(t-1) - \frac{1}{2} \right)$ $x_{k,j}(t-1)$ is called the social component, as it causes the particle to move towards the global best.

3. *Update position*: As shown in Fig. 1, after updating the velocity of each particle, the particle position is updated using the latest updated velocity as:

$$x_{k,i}(t) = v_{k,i}(t) + x_{k,i}(t-1)$$
(18)

- 4. *Update bests*: The fitness of each particle is evaluated according to the newly updated position. If the updated position leads to a better objective function value, the local best and the global best are updated.
- 5. Stopping criteria: The process is repeated until the number of iterations since the last change of the best solution is greater than a pre-specified number, or the number of iterations reaches a maximum allowable number or the desired value of the objective function is reached.

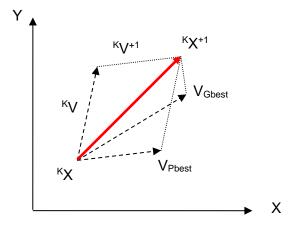


Fig. 1. Construction of the next position.

Fig. 2 shows a flowchart of the PSO algorithm. More details about the PSO algorithm can be found in [23], [24].

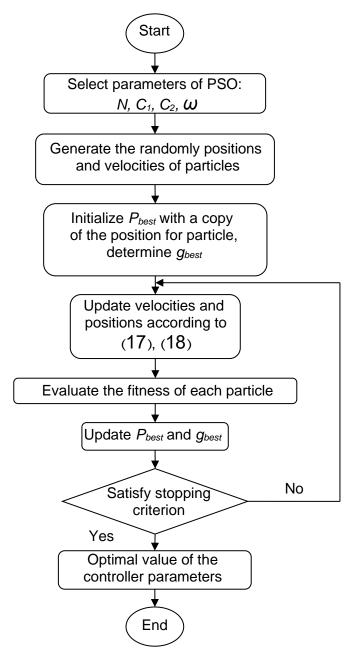
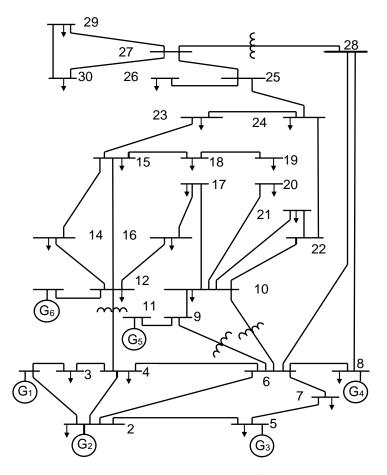


Fig. 2. Flowchart of the PSO algorithm.

4. Case study

In this section, the proposed planning problem is evaluated on the standard IEEE 30-bus 6-generator test system. Several techniques have been tested on this standard system with reported results in the literature. The IEEE 30 bus test case represents a portion of the American electric power system (in the Midwestern US). The system consists of 6 synchronous generators and 4 transformers. The system has 21 load points totalling 283.4 MW and

126.2 Mvar. The detailed system data can be found in. The basic configuration of the IEEE-30 bus system is shown in Fig. 3. The initial transmission network is composed of 29 transmission lines. Seventeen new candidate lines are considered for our study. Table 1 represents the candidate lines data. Project life-time and discount rate are assumed 5 years and 10%, respectively. To demonstrate the effectiveness of utilizing the proposed TEP three scenarios are analyzed. Description of each scenario and the results of the simulations are given below:



 $\textbf{Fig. 3.} \ \textbf{The IEEE 30-bus system configuration}.$

Scenario 1: In this scenario, it is considered that generators production and loads of system is fixed. Here, two objectives as an investment cost and operation cost, are discussed.

Scenario 2: In this scenario, it is considered that generator production can be changed while the system loads are fixed. Investment cost and operation cost as objective functions of the problem are debated.

Scenario 3: In this scenario, Investment cost, operation cost, and cost of load curtailment are objective functions of planning in this scenario. To optimal planning load and generation can be changed.

The results of the proposed planning method are compared with the results of the other methods. In this case, the PSO algorithm is used to solve the proposed planning problem. For this purpose, an initial population of the PSO algorithm is randomly generated, and the investment cost is calculated for each particle. The best particle is chosen, and the velocity of each particle is updated based upon the PSO rules, and eventually, the stop condition of the PSO algorithm is checked. In this paper, the convergence criterion is considered as fifteen iterations in algorithm without any changes in the best fitness. Eventually, by the convergence of PSO, the new lines are determined.

Table 1. Candidates line data.

Candidate lines	From	То	Capacity (MW)	Reactance (p.u.) Susceptance (p.u.)		Investment cost (\$ 10 ⁶ US)
Line 1	2	6	60	0.130	0	22
Line 2	8	15	100	0.04	0.110	21
Line 3	4	18	100	0.04	0.110	19
Line 4	19	28	100	0.05	0.140	35
Line 5	5	6	100	0.0367	0.161	10

Line 6	9	16	100	0.02	0.120	10
Line 7	20	22	100	0.02	0.120	18
Line 8	30	5	100	0.03	0.120	17
Line 9	14	16	100	0.04	0.110	32
Line 10	14	18	100	0.04	0.110	25
Line 11	18	24	100	0.05	0.130	20
Line 12	22	25	100	0.05	0.130	30
Line 13	26	10	100	0.05	0.15	30
Line 14	9	2	100	0.015	0.2	22
Line 15	11	14	100	0.05	0.2	10
Line 16	25	21	100	0.022	0.21	20
Line 17	2	30	100	0.05	0.20	21

Complete results related to the testing case are shown in Table 2. This table shows that 4 and 5 new lines are added for transmission expansion planning in three scenarios, respectively. Figs. 4, 5, and 6 show the convergence of PSO for three scenarios of the proposed method (proposed ACTEP problem). It is clearly seen that the algorithm is converged after hundred iterations. In order to verify the effectiveness of the proposed planning method, the results of the three scenarios are compared. Table 3 shows the

comparative results related to the case study. As shown in this table, the total planning cost in three scenarios is 234.08, 125, and 103.5 ($\$ \times 106$). Where scenario 3 and 2 result 46.59%, 55.78% reduction of total cost compared to scenario 1, which shows a significant reduction compared to scenario 1. This economic aspect of the proposed method clearly emphasizes the priority of the presented planning. It is clearly seen from Table 3 that the proposed method reduces the planning cost.

Table 2. Results for test case.

		Scenar	io 1			Scen	ario 2			Sc	enario	3
Lines addition in AC- TEP		$n_{26-10}, n_{14-18} \ n_{2-30}, n_{20-22}$			$n_{11-14},n_{18-24} \ n_{14-18},n_{25-21}$				$n_{25^{-}21}, n_{11^{-}14}, n_{18^{-}24} \ n_{11^{-}14}, n_{5^{-}6}, n_{9^{-}16},$			
	2.36	x 10 ⁸	ı		L					-		1
	2.358 2.356											
ction (\$)	2.354 2.352											
Objective function (\$)	2.35 2.348											
ÍqO	2.346 2.344		******	(
	2.342			*********			************				**********	*
	2.34	1	0	20	30 4	40 !	50 6	50 7	70 8	30 9	90 1	00

Fig. 4. Convergence of PSO for scenario 1.

Iteration

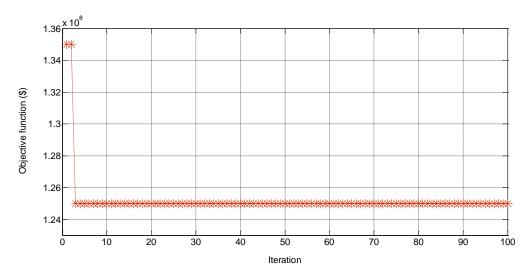


Fig. 5. Convergence of PSO for scenario 2.

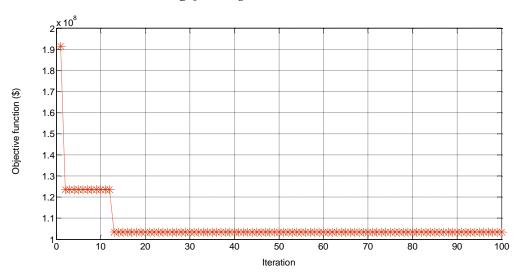


Fig. 6. Convergence of PSO for scenario 3.

Table 3. Comparison of the proposed TEP results.

	Scenario 1	Scenario 2	Scenario 3
Investment cost of the new lines (IC) ($\$ \times 10^6$)	100	75	84
Expected operation costs (EOC) ($\$ \times 10^6$)	134.08	50	17
Cost of load curtailment (CLC) ($\$ \times 10^6$)	-	-	2.49
Total cost of planning (\$ × 10 ⁶)	234.08	125	103.5

5. Conclusion

In this paper, a new expansion planning model for transmission was formulated and applied to a test system. The proposed method allows the power system planners to change the system's topology to reach the best optimal plan for the expanded system in the future. A search algorithm for solving the problem of TEP has been proposed. The

proposed algorithm is tested on the IEEE 30-bus test system as the first attempt for TEP. The results of the case study were shown and completely analyzed. A comparative analysis from the application of the proposed TEP with the previous TEP is presented. The obtained result shows the performance and robustness of the proposed methodology using AC model for solving the TEP problem even in real-

world and large-scale systems. Also, the proposed planning method significantly improves the cost related to TEP.

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REFERENCES

- [1] G. Latorre, R. D. Cruz, J. M. Areiza, and A. Villegas, "Classification of publications and models on transmission expansion planning," *IEEE Transactions on power systems*, vol. 18, no. 2, pp. 938–946, 2003.
- [2] R. Villasana, L. L. Garver, and S. J. Salon, "Transmission network planning using linear programming," *IEEE transactions on power apparatus and systems*, no. 2, pp. 349–356, 1985.
- [3] H. K. Youssef and R. Hackam, "New transmission planning model," *IEEE Transactions on Power Systems*, vol. 4, no. 1, pp. 9–18, 1989.
- [4] N. Alguacil, A. L. Motto, and A. J. Conejo, "Transmission expansion planning: A mixed-integer LP approach," *IEEE Transactions on Power Systems*, vol. 18, no. 3, pp. 1070–1077, 2003.
- [5] V. H. Hinojosa, N. Galleguillos, and B. Nuques, "A simulated rebounding algorithm applied to the multi-stage security-constrained transmission expansion planning in power systems," *International Journal of Electrical Power & Energy Systems*, vol. 47, pp. 168–180, 2013.
- [6] J. R. Barros, A. C. G. Melo, and A. L. da Silva, "Optimization of transmission expansion planning and impact in the reliability tariff—methodology and case study," in *Proc. Symp. Specialists Elect. Oper. Expansion Planning*, 2002.
- [7] R. Romero, C. Rocha, J. R. S. Mantovani, and I. G. Sanchez, "Constructive heuristic algorithm for the DC model in network transmission expansion planning," 2005.
- [8] A. Verma, B. K. Panigrahi, and P. R. Bijwe, "Harmony search algorithm for transmission network expansion planning," *IET generation, transmission & distribution*, vol. 4, no. 6, pp. 663–673, 2010.
- [9] A. M. L. da Silva, L. A. da Fonseca Manso, L. C. de Resende, and L. S. Rezende, "Tabu search applied to transmission expansion planning considering losses and interruption costs," in *Proceedings of the 10th International Conference on Probablistic Methods Applied to Power Systems*, IEEE, 2008, pp. 1–7.

- [10] A. S. D. Braga and J. T. Saraiva, "A multiyear dynamic approach for transmission expansion planning and long-term marginal costs computation," *IEEE Transactions on Power Systems*, vol. 20, no. 3, pp. 1631–1639, 2005.
- [11] S. Binato, G. C. De Oliveira, and J. L. De Araújo, "A greedy randomized adaptive search procedure for transmission expansion planning," *IEEE Transactions on Power Systems*, vol. 16, no. 2, pp. 247–253, 2001.
- [12] J. Contreras and F. F. Wu, "A kernel-oriented algorithm for transmission expansion planning," *IEEE Transactions on Power Systems*, vol. 15, no. 4, pp. 1434–1440, 2000.
- [13] B. Graeber, "Generation and transmission expansion planning in southern Africa," in 1999 IEEE Africon. 5th Africon Conference in Africa (Cat. No. 99CH36342), IEEE, 1999, pp. 983–988.
- [14] X. Ma and Y. Zhou, "Coordination of generation and transmission planning for power system with large wind farms," *Energy Procedia*, vol. 16, pp. 1979–1985, 2012.
- [15] I. Sharan and R. Balasubramanian, "Integrated generation and transmission expansion planning including power and fuel transportation constraints," *Energy Policy*, vol. 43, pp. 275–284, 2012.
- [16] D. Delgado and J. Claro, "Transmission network expansion planning under demand uncertainty and risk aversion," *International Journal of Electrical Power & Energy Systems*, vol. 44, no. 1, pp. 696–702, 2013.
- [17] N. Gupta, R. Shekhar, and P. K. Kalra, "Congestion management based roulette wheel simulation for optimal capacity selection: Probabilistic transmission expansion planning," *International Journal of Electrical Power & Energy Systems*, vol. 43, no. 1, pp. 1259–1266, 2012.
- [18] T. Akbari, M. Heidarizadeh, M. A. Siab, and M. Abroshan, "Towards integrated planning: Simultaneous transmission and substation expansion planning," *Electric Power Systems Research*, vol. 86, pp. 131–139, 2012.
- [19] R.-A. Hooshmand, R. Hemmati, and M. Parastegari, "Combination of AC transmission expansion planning and reactive power planning in the restructured power system," *Energy Convers Manag*, vol. 55, pp. 26–35, 2012.
- [20] A. Mahmoudabadi and M. Rashidinejad, "An application of hybrid heuristic method to solve concurrent transmission network expansion and reactive power planning," *International Journal of Electrical Power & Energy Systems*, vol. 45, no. 1, pp. 71–77, 2013.
- [21] A. Akbarimajd, M. Olyaee, H. Shayeghi, and B. Sobhani, "Distributed multi-agent Load Frequency Control for a Large-scale Power System Optimized by Grey Wolf Optimizer," *Journal of Operation and Automation in Power Engineering*, vol. 5, no. 2, pp.

- 151-162, 2017.
- [22] H. Shayeghi, B. Sobhany, and M. Moradzadeh, "Management of Autonomous Microgrids Using Multi-Agent Based Online Optimized NF-PID Controller," *Journal of Energy Management and Technology*, vol. 1, no. 1, pp. 79–87, 2017.
 [23] M. A. M. De Oca, T. Stutzle, M. Birattari, and M.
- [23] M. A. M. De Oca, T. Stutzle, M. Birattari, and M. Dorigo, "Frankenstein's PSO: a composite particle swarm optimization algorithm," *IEEE Transactions on Evolutionary Computation*, vol. 13, no. 5, pp. 1120–1132, 2009.
- [24] D. Wang, D. Tan, and L. Liu, "Particle swarm optimization algorithm: an overview," *Soft comput*, vol. 22, pp. 387–408, 2018.