Stochastic Transmission Expansion Planning Incorporating Reliability Solved Using SFLA Meta-heuristic Optimization Technique

Saedeh Alaee, Rahmat-Allah Hooshmand, *Senior Member*, *IEEE*, and Reza Hemmati

***Abstract*—This paper addresses stochastic transmission expansion planning (TEP) under uncertain load conditions when reliability is taken into consideration. The main objective of the proposed TEP is to minimize the total planning cost by denoting the place, number, and type of new transmission lines subject to safe operation criteria. In this paper, the objective function consists of two terms, namely, investment cost (IC) of new lines and reliability cost. The reliability cost is incorporated as the loss of load cost (LOLC). Network uncertainties in the form of loads are molded as Gaussian probability distribution function (PDF). Monte-Carlo simulation is applied to tackle the uncertainties. The proposed stochastic TEP is expressed as constrained optimization planning and solved using shuffled frog leaping algorithm (SFLA) SFLA is compared to other optimization techniques such as particle swarm optimization (PSO) and genetic algorithms (GA). Finally, stochastic planning (planning including uncertainty) and deterministic planning (planning excluding uncertainty) are compared to demonstrate impacts of uncertainty on the results. Simulation results in different cases and scenarios verify the effectiveness and viability of the proposed stochastic TEP, including uncertainty and reliability.**

***Index Terms*—Reliability, shuffled frog leaping algorithm, stochastic planning, transmission expansion planning, uncertainty.**

NOMENCLATURE

A. Symbols

$\boldsymbol{c}$	Vector showing investment cost (IC) of new lines.
$\boldsymbol{n}$	Vector showing installed lines.
α	Loss of load cost (\$/MWh).
$P_i^{y,l}(V,\theta,n)$	Active power of all lines connected to bus i during year$y$ at load level l.
$Q_i^{y,l}(V,\theta,n)$	Reactive power of all lines connected to bus i during year y at load level l.
$\boldsymbol{\theta}$	Phase angle vector.
$\boldsymbol{v}$	Voltage amplitude vector.
$P_{\mathrm{G}_i}^{y,l}$	Generation active power of bus i during year y at load level l.
$P_{\mathrm{D}_i}^{y,l}$	Consumption active power of bus i during year y at load level l.
$Q_{\mathrm{G}_i}^{y,l}$	Generation reactive powers of bus i during year$y$ at load level l.
$Q_{\mathrm{D}_i}^{y,l}$	Consumption reactive powers of bus i during year y at load level l.
NB	Number of buses.
T	Planning horizon.
L	Number of load levels, respectively.
NG	Number of generators of network.
NR	Number of reactive power resources.
$\boldsymbol{N}_{0ij}$	Diagonal matrices of new lines installed in network between i,j buses.
$\boldsymbol{N}_{ij}$	Diagonal matrices of exiting lines installed in network between i,j buses.
S_{ij}^{from}	Sending apparent powers from bus i to us j.
S_{ij}^{to}	Receiving apparent powers from bus i to us j.
$S_{ij}^{\max}$	Maximum permitted apparent power of line between buses i,j.
n_{ij}	Number of lines in corridor between buses i,j.
$n_{\mathrm{ij}}^{\max}$	Maximum number of installed lines in corridor between buses i,j.
$\boldsymbol{X}_{\mathrm{g}}$	Frogs with the best fitness in total population.
$\boldsymbol{X}_{\mathrm{b}}$	Frogs with the best fitness in Memeplex.
$\boldsymbol{X}_{\mathrm{w}}$	Frogs with the worst fitness in Memeplex.
r	Random number ranging [0, 1].
C	Constant ranging 1 to 2.
r_i	Random values ranging 1, -1.
$w_{i,\max}$	Maximum allowable movement in next searching space i.
$D_{\max}$	Maximum allowed distance of leaping.

B. Abbreviations

LOLC	Loss of load cost.
IC	Investment cost.
EENS	Energy expected not supplied.
SFLA	Shuffled frog leaping algorithm.
PSO	Particle swarm optimization.
GA	Genetic algorithm.

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S. Alaee and R.-A. Hooshmand (corresponding author, e-mail: Hooshmand_r@eng.ui.ac.ir) are with the Department of Electrical Engineering, University of Isfahan, Isfahan, Iran.

R. Hemmati is with the Department of Electrical Engineering, Kermanshah University of Technology, Kermanshah, Iran.

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I. INTRODUCTION

OPTIMAL expansion of power systems is a critical issue in electric power systems. Expansion planning can be performed in the generation, transmission or distribution sectors [1], [2]. Transmission expansion planning (TEP) is unavoidable in the context of long-term planning of electric power systems. The goal of TEP is to develop the existing system in ways that it satisfies demand growth for future years. Furthermore, energy resources such as wind farms and hydro power plants are typically located far from load centers where the transmission capacity is inadequate. In order to transfer the energy, new lines need to be installed or existing networks reinforced. In this regard, TEP denotes where, when, and how many new lines should be installed in the network to satisfy the predicted demand, subject to reliability-security criteria, and economical-operation conditions [3].

Since TEP is generally expressed as a mixed integer non-linear programming (MINLP), solving the TEP and determining the optimal solution for large-scale systems is challenging. Many studies have been conducted on TEP to provide new and efficient solutions [3]–[16]. Solving methods for TEP can be classified as mathematical optimization approaches comprising mixed integer programming [3], linear programming [4], [5], non-linear programming [6], and meta-heuristic optimization techniques such as dynamic programming [7], ant colony algorithm [8], artificial immune system [9], artificial neural networks [10], chaos and honey bee algorithm [11], differential evolution [12], frog leaping algorithm [13], genetic algorithm [14], harmony search algorithm [15], PSO, Tabu, and annealing search [16]. Many objective functions and constraints have also been developed for TEP. In traditional planning, the objective function is to minimize the investment cost (IC) of new lines. The new electricity market structure has furthermore raised new issues and constraints for TEP, some of which are in contradiction to each other [3].

Reliability is yet another issue that needs to be incorporated into TEP. Since TEP is designed for long-term planning, taking reliability into consideration for such planning is required to meet future loads. In TEP, reliability can be considered a constraint or as a part of an objective function [8], [17]–[19]. However, including reliability in the objective function of planning is more effective [3].

Uncertainty is another important and practical issue, which is typically incorporated into TEP. Taking uncertainties into account minimizes risks associated with planning and leads to a flexible plan [3]. In this regard, load uncertainty is considered in TEP as a typical uncertainty in practical electric power systems. Load uncertainties lead to a robust plan and satisfy the demand under a planning horizon [20]. The uncertainties related to renewable generations, such as wind and solar units can also be included in TEP [21]. Mathematical-probabilistic modeling or Monte-Carlo simulation are the tools used for determining uncertainties in TEP, with the former requiring less time, and the latter being much easier in terms of applications [3], [22].

TEP is mainly modeled based on AC or DC load flow models. The AC model is a complete model based on AC load flow equations and includes reactive power [17], [23], [24], while the DC model applies DC load flow equations without reactive power and is a simple model [1], [6], [18], [25]. This paper presents transmission network expansion planning under load uncertainty. The proposed TEP also aims at minimizing investment costs and reliability costs at the same time. The AC model is used for load flow studies. Application of the AC model leads to a complex non-linear planning problem, which is solved using the SFLA technique.

SFLA is a very strong optimization technique widely applied to electric power system problems such as unit commitment [26], optimal power flow [27], probabilistic three-phase load flow in unbalanced distribution systems [28], and optimal switch placement in distribution automation systems [29]. SFLA solutions are validated by comparing to GA and PSO. All practical constraints comprising voltage limitation, active and reactive power constraints, transmission line capacity, and power balance at all buses are considered in the planning to demonstrate that the proposed method is capable of providing an optimal TEP under uncertainties, including reliability. The main contributions of this paper are as follows:

1) This paper addresses stochastic TEP including high-level penetration of uncertainties and Monte-Carlo simulation applied to deal with these uncertainties.
2) Studies available in the literature mostly consider reliability as a constraint in problems, but in the present study, reliability is considered as a part of an objective function to be optimized.
3) Static constraints of the network such as the maximum capacity of lines, reactive power limit of generators, balance equations of active and reactive powers at all buses, and voltage limits of buses are also considered in the planning.
4) While there are studies that apply DC load flow to planning by excluding reactive power, this work utilizes AC load flow that takes into account reactive power.
5) This work also factors in several nonlinear constraints, as well as the AC load flow, which leads to a very nonlinear and complex optimization problem. As such, SFLA, which is a strong optimization technique, is used to solve the problem.

It is worth noting that the above issues interact in different ways with various outcomes, as presented in this paper. The advantage of including all these issues in one paper is to provide more accurate and real results. For instance, considering reliability together with AC power flow leads to including reactive power in the reliability calculations and providing more real results. The reactive power can also impact network constraints such as line capacity, bus voltage, etc. Therefore, considering all practical constraints along with AC power flow is a great challenge and this paper successfully tackles such a challenge to provide more acceptable and guaranteed results. Apart from this introductory section, this paper is organized as follows: Section II is devoted to problem modeling. Section II presents the proposed stochastic programming including uncertainty. In Section IV, the FLA method is presented. Simulation results are given in Section V. A conclusion and discussions are presented in Section VI.

II. Problem Modeling

TEP is constrained mixed integer nonlinear programming (MINLP) as expressed through (1) to (9):

$$\text{Min obj} = \boldsymbol{c}^{\mathrm{t}}\boldsymbol{n} + \sum_{y=1}^{T}\sum_{l=1}^{L} LOLC^{y,l} \tag{1}$$

Subject to

$$P_{\mathrm{G}_i}^{y,l} - P_{\mathrm{D}_i}^{y,l} = P_i^{y,l}(V,\theta,n) \quad i \in NB, y \in T, l \in L \tag{2}$$

$$Q_{\mathrm{G}_i}^{y,l} - Q_{\mathrm{D}_i}^{y,l} = Q_i^{y,l}(V,\theta,n) \quad i \in NB, y \in T, l \in L \tag{3}$$

$$P_{\mathrm{G}_j}^{\min} \le P_{\mathrm{G}_j}^{y,l} \le P_{\mathrm{G}_j}^{\max} \quad j \in NG, y \in T, l \in L \tag{4}$$

$$Q_{\mathrm{G}_j}^{\min} \le Q_{\mathrm{G}_j}^{y,l} \le Q_{\mathrm{G}_j}^{\max} \quad j \in (NG+NR), y \in T, l \in L \tag{5}$$

$$V_i^{\min} \le V_i^{y,l} \le V_i^{\max} \quad i \in NB, y \in T, l \in L \tag{6}$$

$$(S_{ij}^{\mathrm{from}})^{y,l} \le S_{ij}^{\max} \tag{7}$$

$$(S_{ij}^{\mathrm{to}})^{y,l} \le S_{ij}^{\max} \tag{8}$$

$$0 \le n_{ij} \le n_{ij}^{\max} \quad i,j \in NB. \tag{9}$$

Objective function (1) comprises two terms. The first term indicates the investment cost of new installed lines and the second term represents the reliability cost given as loss of load cost (LOLC). It is worth mentioning that ‘t’ is the vector transpose of cost, and *LOLC* is calculated as follows:

$$LOLC = EENS \times \alpha. \tag{10}$$

AC power flow equations are expressed through constraints (2) and (3). These equations indicate the equilibrium of active and reactive powers at all buses including loss in transmission lines. It is worth mentioning that the satisfaction of these two constraints means the network power flow is converged. The limitations of active and reactive power of generators are specified in (4) and (5), respectively. Bus voltage limitation is given by (6). The maximum capacity of the lines is expressed by (7) and (8). It is worth mentioning that when the maximum power in a corridor is checked, the exiting lines ($\boldsymbol{N}_{ij}$) as well as the new installed lines ($\boldsymbol{N}_{0ij}$) are included. Constraint (9) specifies the maximum permitted lines in each corridor.

III. Stochastic Programming Including Uncertainty

In the proposed TEP, loads are considered as uncertain parameters and modeled as Gaussian probability distribution function (PDF). Then, scenario-based Monte-Carlo simulation is utilized to tackle such uncertainty in planning. This issue leads to a stochastic TEP shown in Fig. 1. The details of this flowchart are as follows:

Block A: In this stage, an individual from the initial population is selected for evaluation.

Block B: Here, a Gaussian PDF is generated for uncertain parameters (i.e., loads). Then, a large number of scenarios are produced by sampling based on the Gaussian PDFs. Sampling is done based on the Monte-Carlo sampling technique that generates a random number based on Gaussian PDFs while using the MATLAB software.

Block C: In this block, AC power flow is carried out for each generated scenario in the previous block (block B). Converging AC power means that all security constraints such as voltage and power limitations are satisfied.

Block D: Here, objective function (1) is calculated for each generated scenario in block B. First term of (1) shows the investment cost on new lines and the second term indicates the reliability cost or LOLC cost. Reliability cost is calculated at each load level and then total LOLC cost related to all load levels is calculated. After calculating total LOLC cost related to one year, LOLC cost over the planning horizon is calculated. The proposed LOLC cost over the planning horizon is added to the investment cost on new lines to make the final objective function related to each performance scenario. Therefore, there is only one objective function for all load levels according to (1).

Block E: Convergence of Monte-Carlo simulation is checked based on the maximum pre-defined sampling numbers. If a criterion is met, the algorithm will go to the next block; otherwise it will go to block B.

Block F: Here, the objective function is calculated for the current individual in the population. The objec-

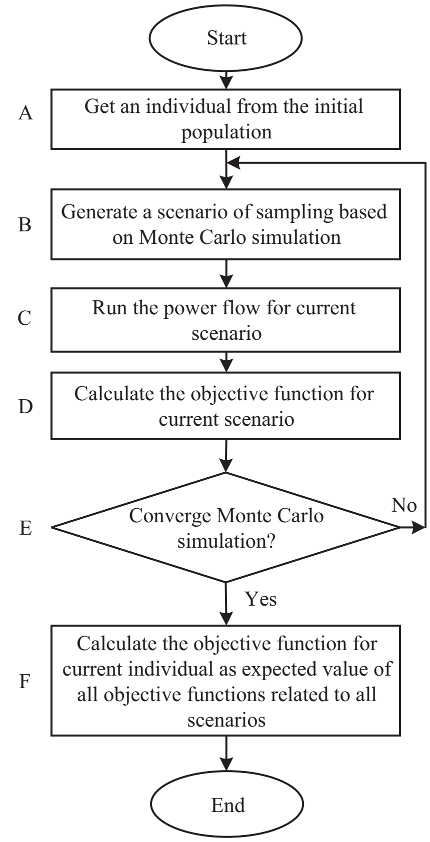

Fig. 1. Proposed algorithm of transmission expansion planning considering load uncertainty.

tive function of each individual is equal to the expected value of all objective functions related to all the scenarios.

IV. SFLA Technique

In the SFLA technique, an initial population is first generated, which is then divided into several equal groups. The frogs in each group perform a local search and improve their location toward food and find the optimal local solution. Then the knowledge between the groups is exchanged and the information compared with each other. The best knowledge is then chosen, with the iteration continuing until convergence.

The SFLA technique flowchart is depicted in Fig. 2. First the initial population including P member is generated randomly. Then the objective function is calculated for all members. In the next step, the population is divided into m groups (Memeplex), each one including n members and where the elite members are distributed among all groups.

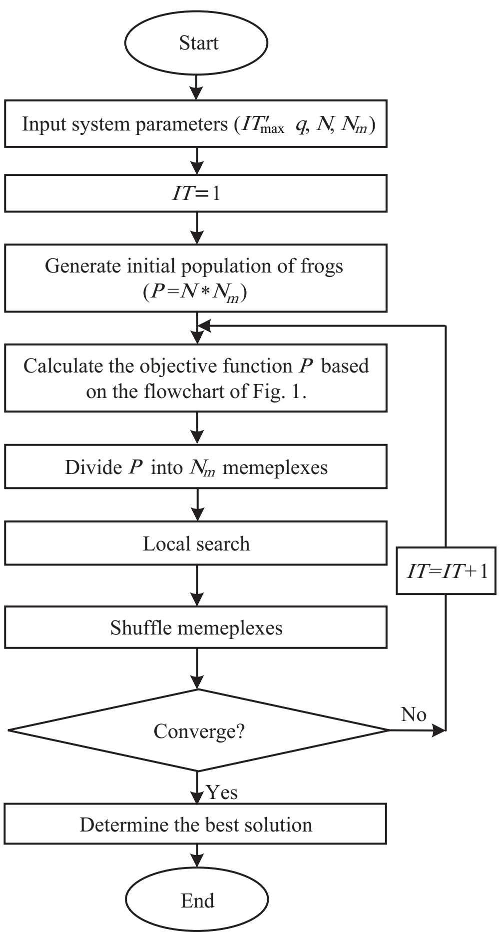

Fig. 2. Flowchart showing SFLA technique in general.

Based on the selection of the best Memeplex, as it can be locally optimized, it is better to consider a subset of Memeplexes called sub-memeplex. The strategy for selecting the sub-memeplexes is to give smaller coefficients to frogs with low executive value and higher coefficients to frogs with high executive value. Then local searching is used for leaping of the frogs from the worst fitness to the best fitness. After applying local searching, the new frog can replace the worst frog if it has better response; otherwise the process is repeated. If by applying changes, no suitable response is found, an answer is generated randomly, which can be used instead of the worst member of the group. This trend continues for the number of defined iterations to obtain the conditions of the ending algorithm. The frog leaping rule in this algorithm is as follows [29]:

$$\boldsymbol{X}_{\mathrm{w}}^{\mathrm{new}} = \boldsymbol{X}_{\mathrm{w}} + \boldsymbol{D}, |\boldsymbol{D}| < D_{\max} \tag{11}$$

$$\boldsymbol{D} = r\boldsymbol{c}(\boldsymbol{X}_{\mathrm{b}} - \boldsymbol{X}_{\mathrm{w}}) + \boldsymbol{W} \tag{12}$$

$$\boldsymbol{W} = [r_1 w_{1,\max}, r_2 w_{1,\max}, \ldots, r_s w_{s,\max}]^{\mathrm{T}}. \tag{13}$$

A. Relations Among Different Blocks in Fig. 1 and Fig. 2

Fig. 1 depicts the proposed algorithm of TEP considering uncertainty, while Fig. 2 shows the flowchart of the general SFLA technique. In Fig. 2, an initial population is generated and then the objective function (1) is calculated for each individual of the population as shown in the fifth block of Fig. 2 (i.e., calculate the objective function P based on the flowchart of Fig. 1). Then the SFLA rules are carried out and eventually the SFLA convergence is applied and the best solution is chosen.

V. Simulation Results

The proposed algorithm is simulated on two test cases: a 6-bus Garver network and IEEE 24-bus test system. The system data were derived from [30]. The simulation was carried out in MATLAB software on a PC with the following information: memory 4 G, 5-core CPU, and 2.30 GHz. In the first section, the validity and efficiency of SFLA algorithm was investigated. Then, two cases were simulated: a network with uncertainty (stochastic planning) and a network without uncertainty (deterministic planning). In each section, the impact of reliability on the problem was also investigated.

A. Validating the Solving Method (SFLA Technique)

In order to validate the solving method (SFLA technique), planning was run with similar conditions as in [23] in which a 6-bus test system depicted in Fig. 3 was considered as the

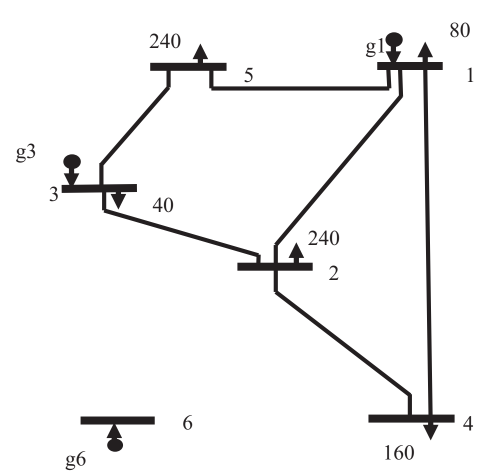

Fig. 3. Single line diagram of six-bus test system (so called Garver network).

case study. The purpose was to connect bus 6 to the network, and the objective function was to minimize the investment cost of new lines. Planning was run using three optimization algorithms: SFLA, PSO, and GA. Table I, shows the results. Based on the results, it is clear that all algorithms resulted in similar plans such as [23]. The simulation times of SFLA, PSO, and GA are 6, 30, and 40 minutes, respectively. It is seen that the SFLA algorithm takes less simulation time and is therefore quicker than PSO, GA, and as those in [23].

TABLE I
PLANNING RESULTS USING DIFFERENT SOLVING METHODS

Methods	Installed Lines	IC ($, million)
The proposed method by SFLA, PSO, GA	$n_{3\text{-}5} = 2$, $n_{2\text{-}6} = 2$, $n_{4\text{-}6} = 2$	160
Reference [23]	$n_{3\text{-}5} = 2$, $n_{2\text{-}6} = 2$, $n_{4\text{-}6} = 2$	160

B. Deterministic Planning

In order to simulate the proposed method, a modified version of the network shown in Fig. 3 is considered as a case study. Fig. 4 shows a modified version of the network shown in Fig. 3. Annual load growth is equal to 4% and a five-year horizon is considered. With regards to the load growth, although the network is satisfactory from the perspective of generation, the transmission capacity is inadequate, and the network needs to install new lines. Here, the objective function is considered as investment cost (IC) of new lines and loss of load cost (LOLC). The results of planning are listed in Table II. Furthermore, the convergence process of algorithms in depicted in Fig. 5. The results show that the SFLA algorithm is better than the PSO method, leading to a more optimal plan, and where total SFLA planning cost is $1 million less than the other methods. Although PSO converges on fewer iterations, it takes more simulation time; whereas the simulation time of SFLA is approximately 15 s and PSO about 30 s.

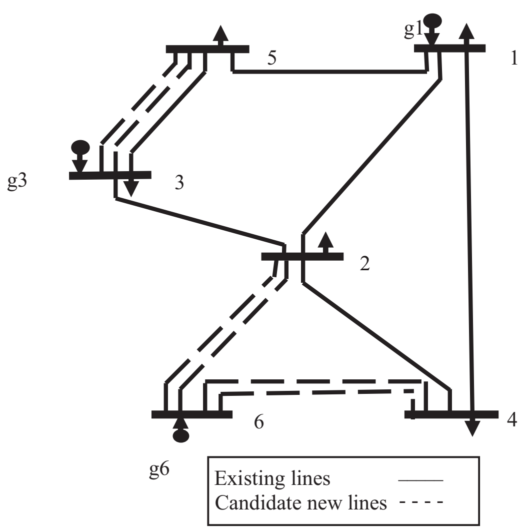

Fig. 4. Expansion planning for first stage.

To investigate the impact of reliability on the planning, two types of planning, i.e., "with" and "without" reliability are

TABLE II
PLANNING RESULTS OF DETERMINISTIC PLANNING

Planning	Installed Lines	IC ($, million)	LOLC ($, million)
SFLA	$n_{1\text{-}5} = 2$, $n_{2\text{-}3} = 1$, $n_{2\text{-}6} = 1$, $n_{3\text{-}5} = 1$, $n_{4\text{-}6} = 1$	160	16.143
PSO	$n_{2\text{-}6} = 1$, $n_{3\text{-}5} = 1$, $n_{4\text{-}6} = 1$, $n_{5\text{-}6} = 1$	161	17.91

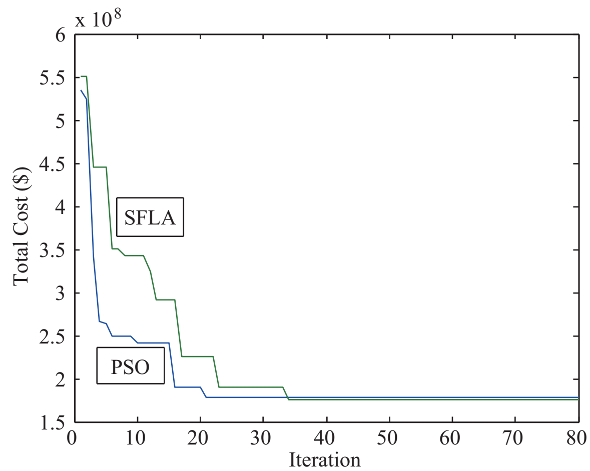

Fig. 5. Convergence process of PSO and SFLA methods.

carried out and results are listed in Table III. As shown in the table, when reliability is factored in, the total investment cost increases from $120 million (planning with only IC) to $176.143 million (planning with IC and LOLC). On the other hand, LOLC of the network when reliability is included is $16.143 million, while LOLC of the network excluding reliability is $107.09 million. As a result, when reliability is included, it increases the total investment cost by $56.143 million, but reduces the LOLC by $90.947 million. It can be concluded then that when reliability is considered, it saves $34.804 million for network operators. By taking into account reliability in the planning, investment cost is increased, but on the other hand, the reliability of the network is significantly improved.

TABLE III
PLANNING RESULTS OF DETERMINISTIC PLANNING WITH AND WITHOUT RELIABILITY COST IN THE OBJECTIVE FUNCTION

Objective Function	Installed Lines	IC ($, million)	LOLC ($, million)
IC	$n_{1\text{-}5} = 1$, $n_{2\text{-}6} = 1$, $n_{3\text{-}5} = 1$, $n_{4\text{-}6} = 1$	120	107.09
IC and LOLC	$n_{1\text{-}5} = 2$, $n_{2\text{-}3} = 1$, $n_{2\text{-}6} = 1$, $n_{3\text{-}5} = 1$, $n_{4\text{-}6} = 1$	160	16.143

C. Stochastic Planning

To implement stochastic planning under load uncertainties, two major loads of the network (loads on bus 2 and bus 5) are considered as uncertain loads and approximated by three load levels. Since there are two uncertain loads and three load levels for each load, nine scenarios are obtained to cover the uncertainty area of the problem. Furthermore, in order to investigate uncertainty levels on the TEP problem, scenarios of uncertainty are defined as 5, 10, and 15 percent uncertainties.

1) Planning with 10 % Load Uncertainty

In this case, the loads are considered as standard Gaussian probability distribution function (PDF) by 10% standard deviation. As stated before, each load is modeled at three loads levels. Table IV shows these loads levels and the related probabilities for uncertain loads on bus 2 and bus 5. As a result, there are nine scenarios of uncertainties as listed in Table V. Table VI demonstrates the stochastic expansion planning under such uncertainties. It is clear that the selected lines for expansion are installed from bus 2 or bus 5 (the buses including uncertain loads) toward the other buses. This issue demonstrates that the buses installed with uncertain loads need to reinforce their connection with the network to tackle the uncertainty.

TABLE IV
APPROXIMATED MODEL OF UNCERTAIN LOADS INCLUDING 10% UNCERTAINTY BY THREE LOAD LEVELS

Load Level for Loads on Bus 2 and Bus 5 (MW)	Probability
263.7	0.1587
293	0.6827
322.3	0.1587

TABLE V
LOAD UNCERTAINTY SCENARIOS WITH RESPECT TO THE LOAD LEVELS IN TABLE IV

Scenario Number	Load of Bus 2 (MW)	Load of Bus 5 (MW)	Probability
1	263.7	263.7	0.0252
2	263.7	293	0.1083
3	263.7	322.3	0.0252
4	293	263.7	0.1083
5	293	293	0.4661
6	293	322.3	0.1083
7	322.3	263.7	0.0252
8	322.3	293	0.1083
9	322.3	322.3	0.0252

TABLE VI
COMPARING DETERMINISTIC AND STOCHASTIC PLANNING

Planning	Installed Lines	IC ($, million)	LOLC ($, million)
Deterministic	$n_{1\text{-}5}=2$, $n_{2\text{-}3}=1$, $n_{2\text{-}6}=1$, $n_{3\text{-}5}=1$, $n_{4\text{-}6}=1$	160	16.143
Stochastic (5% uncertainty)	$n_{1\text{-}5}=2$, $n_{2\text{-}3}=2$, $n_{2\text{-}6}=1$, $n_{3\text{-}5}=1$, $n_{4\text{-}6}=1$, $n_{3\text{-}6}=1$	228	6.268
Stochastic (10% uncertainty)	$n_{1\text{-}5}=2$, $n_{2\text{-}3}=2$, $n_{2\text{-}6}=1$, $n_{3\text{-}5}=1$, $n_{4\text{-}6}=1$, $n_{5\text{-}6}=1$	241	1.027
Stochastic (15% uncertainty)	$n_{1\text{-}5}=2$, $n_{2\text{-}3}=2$, $n_{2\text{-}6}=1$, $n_{3\text{-}5}=1$, $n_{4\text{-}6}=1$, $n_{5\text{-}6}=2$	302	2.28

2) Planning with 5 and 15% Load Uncertainty

In this section, the previous process is repeated for 5% and 15% load uncertainties. For an easy comparison, a summary of stochastic and deterministic results is shown in Table VI. It is clear that by increasing uncertainty, the planning cost is increased to tackle the uncertainty. In addition, under deterministic planning, LOLC is very high, while stochastic planning thoroughly reduces the LOLC due to its robust planning.

D. Comparing Deterministic and Stochastic Planning

With regards to Table VI and when comparing deterministic planning to stochastic planning with 5% uncertainty, it can be seen that the stochastic plan installs two additional lines in the network comprising lines in corridors 2–3 and 3–6. These two connections are made between generating buses (bus 3 is a major generating bus) and uncertain loads, creating the capacity to adjust to load uncertainty. Based on the results, stochastic planning satisfactorily tackles the uncertainty in the network. Furthermore, stochastic planning that is under 10% uncertain conditions installs 2 extra lines in corridors 2–3 and 5–6.

The superiority of stochastic planning over deterministic planning is demonstrated when power flow is carried out for both plans under all scenarios, as listed in Table V. The results indicate that power flow in stochastic planning converges under all scenarios and can support the load under all scenarios. On the other hand, four scenarios of Table V, and this planning cannot successfully support the load including uncertainty. The voltage profile on all the buses is depicted in Fig. 6.

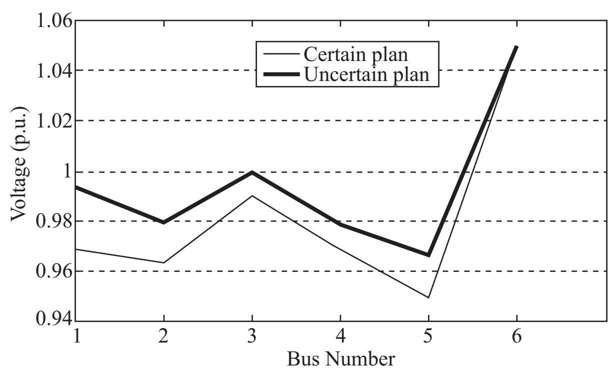

Fig. 6. Voltage profile on all buses under fifth loading scenario.

It is clear that stochastic planning provides better voltage profile over deterministic planning. By comparing stochastic planning under 10% uncertainty to deterministic planning, it can be stated that stochastic planning installs three extra lines, one line in corridor 2–3, and two lines in corridor 5–6. This extra investment cost and reinforcement successfully tackles the network uncertainties. As a result, accompanied by increasing uncertainty levels in the network, the operator has to install more lines and invest more budgets on the network.

E. Planning on IEEE 24 Bus Test System

The proposed planning was carried out on an IEEE 24 bus test system. Loads on buses 8 and 14 were modeled as Gaussian loads by 20% standard deviation. Table VII shows the planning outcome under stochastic cases. It is clear that the planning includes installation of one line, from bus 1 to bus 8 (i.e., the bus that includes the uncertain load) to tackle load uncertainties. Furthermore, LOLC is significantly low following such expansion, thus validating the method. Fig. 7 shows the network after expansion and installation of new lines.

TABLE VII
PLANNING OUTPUT ON IEEE 24 BUS TEST SYSTEM

Candidate Lines	Installed Lines	LOLC ($, thousand)	IC ($, million)
$n_{1\text{-}8} = 1$; $n_{2\text{-}8} = 1$; $n_{14\text{-}23} = 1$; $n_{13\text{-}14} = 1$	$n_{1\text{-}8} = 1$	7	33

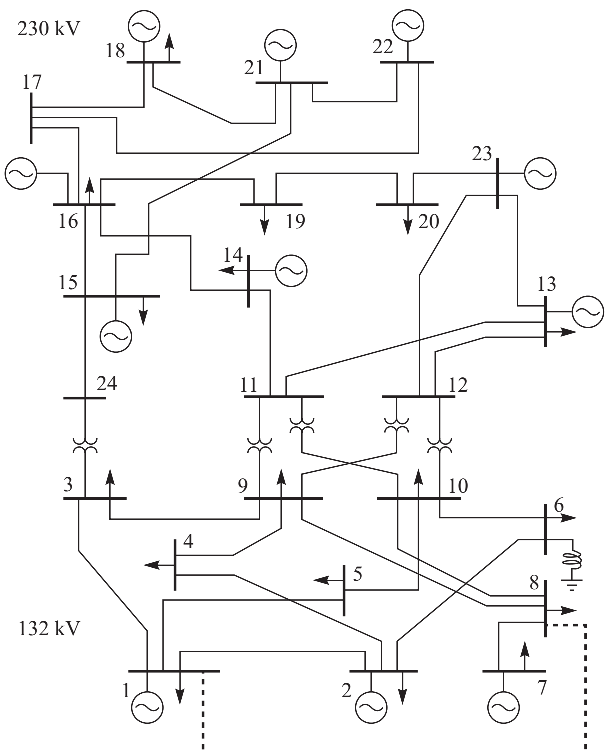

Fig. 7. IEEE 24 bus test system after expansion (dashed line shows the new installed line).

VI. CONCLUSION

In this paper, a new method for TEP is addressed to minimize investment cost of new lines, as well as loss of load cost. The uncertainty in loads is included in the planning, and the basic constraints of the network are considered. The planning is mathematically expressed as a constrained optimization program and solved using the SFLA technique. Based on the results, when reliability is considered, it increases the investment cost, but on the other hand, significantly improves the reliability and performance of the network. By considering load uncertainty in the planning, more lines are required to be installed to cope with load uncertainty and fluctuations, thus also increasing the investment cost. Furthermore, comparing meta-heuristic optimization algorithms for the proposed TEP shows that SFLA is faster and more appropriate than PSO and GA approaches.

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Saedeh Alaee was born in Isfahan, Iran, in 1988. She received the B.S. degree in electrical engineering from Isfahan University of Technology, Isfahan, Iran, in 2010, the M.S. degree in electrical engineering from Isfahan University, Isfahan, Iran, in 2014. Her research interests include power systems planning and operation.

Rahmat-Allah Hooshmand (M'10) received the B.Sc. degree from University of Mashhad in 1989, the M.Sc. degree from University of Tehran, Iran, and PhD degree from Tarbiat Modarres University, Iran, in 1990 and 1995, respectively, all in electrical engineering. He is currently Associate Professor in Electrical Engineering Department, University of Isfahan, Iran. His main research interests are modeling of power systems and distribution networks.

Reza Hemmati received the PhD degree in electrical engineering from University of Isfahan, Isfahan, Iran, in 2014. Presently, he is with the department of electrical engineering at Kermanshah University of technology, Kermanshah, Iran. His research interests include power systems planning, operation, and control.