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A New Risk-managed Planning of Electric Distribution Network Incorporating Customer Engagement and Temporary Solutions

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***Abstract*— The connection of renewable-based distributed generation (DG) in distribution networks has been increasing over the last few decades, which would result in increased network capacity to handle their uncertainties along with uncertainties associated with demand forecast. Temporary non-network solutions (NNSs) such as demand response (DR) and temporary energy storage system (ESS)/DG are considered as promising options for handling these uncertainties at a lower cost than network alternatives. In order to manage and treat the risk associated with these uncertainties using NNSs, this paper presents a new risk-managed approach for multi-stage distribution expansion planning (MSDEP) at a lower cost. In this approach, the uncertainty of available DR is also taken into account. The philosophy of the proposed approach is to find the "optimal level of demand" for each year at which the network should be upgraded using network solutions (NSs) while procuring temporary NNSs to supply the excess demand above this level. A recently developed forward-backward approach is fitted to solve the risk-managed MSDEP model presented here for real sized networks with a manageable computational cost. Simulation results of two case studies, IEEE 13-bus and a realistic 747-bus distribution network, illustrate the effectiveness of the proposed approach.**

***Index Terms*—Demand response, Energy storage, Multi-stage electric network distribution planning, Risk-managed cost, Uncertainty, Probability of exceedance.**

I. Introduction

The cost of electric networks, including investment and operation costs, is over 50% of the customer electricity bill in Australia [1], reflecting a large investment in distribution networks to meet increasing peak demand, to replace aging assets, and to meet higher reliability standards. The current electricity network reliability standards in the country require extra network infrastructure to be built to achieve a high reliability of supply. These reliability standards and conservative (high) prediction of future peak demand have driven over-investments in the network. In addition, renewable energy targets are set by nations to develop a rapid uptake of green energy sources, for example, 23.5% contribution of renewables by 2020 in Australia's electricity generation [2]. Therefore, it is expected this investment situation becomes worse as more and more variable generation such as photovoltaics (PVs) are integrated within distribution networks to meet the country's renewable energy targets. This is because grid requires additional network capacity to tackle the uncertainties of variable renewable sources. With increased uncertainties in the system, new planning tools that incorporate risk management into distribution network planning are required, enabling network planners to make informed decisions on network augmentation in the most cost-effective manner.

The temporary or short-term non-network solutions (NNSs) are considered as a promising option to manage risks arising from load and renewable generation uncertainties. The cost-effectiveness of NNSs to manage these risks needs to be evaluated within a long-term network plan. This long-term plan looks at whether and how much to use NNSs as part of the plan by determining the bounds of the trade-off between savings due to the postponement of investment of NSs versus the cost of temporary NNSs. In this context, this paper presents a novel long-term multi-stage distribution expansion planning (MSDEP) approach, which is able to produce a plan with an optimal combination of NSs and NNSs. This is carried out by determining the optimal level of demand at which the network should be upgraded using NSs while procuring temporary NNSs to meet demand exceeding this level.

The MSDEP methods have been a topic of interest over last four decades as MSDEP problems are complex combinatorial problems due to a large number of variables involved. With the transition of passive distribution networks to active distribution networks in the presence of distributed energy systems (DESs), the complexities of MSDEP problems have increased further due to higher uncertainties involved with them. The MSDEP model for real sized active networks consists of three complexity dimensions, which are a) large problem size, b) time dynamic nature, and c) increased uncertainties due to DESs. Different approaches have been used in the literature to handle these complexities. Heuristics approaches such as tabu search [3], particle swarm optimization (PSO) [4-8], and genetic algorithm (GA) [9-11] have been used to handle large problem sizes. While, decomposition techniques such as forward filling [12], backward pull-out [13], and recursive forward-backward approach [4], [5], [11], [14] have been used for handling time dynamics of MSDEP problems. The uncertainties of load and renewable generation have been modeled either using probability distribution functions (PDF) based on the available

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historical probabilistic data [7] or by generating possible scenarios based on experience and knowledge [11], [15-21] when the probabilistic data is not available or using a hybrid possibilistic–probabilistic model [22].

A tabu search based MSDEP is presented to optimize the total investment, operational, and reliability of distribution networks by upgrading transformers, lines, and tie lines including switches [3]. A modified PSO is proposed to solve MSDEP considering loss and reliability of networks through the use of dispatchable DGs [8]. For optimal usage of ESSs and voltage control devices such voltage regulators and capacitors along with conventional upgrades, an efficient forward-backward algorithm is given in [4], which is extended to consider the reconfiguration of the network in [5]. The inclusion of DGs in MSDEP along with the possible change to lines such as addition, removing, combining, and replacing of lines is investigated in [12]. In addition, a backward approach is proposed to find location and size of DGs, along with substations and feeders [13]. Nara et al. propose a recursive forward-backward approach for MSDEP using the branch and bound method. In this approach, forward fill-in approach is initiated from the first time stage and proceeded to the next second stage and then backward is tried. If a better expansion plan cannot be obtained from the backward path, the forward path proceeds to the next time stage, and the procedure goes on. This procedure is done recursively until finding the best solution [14]. However, theses references do not consider uncertainty of load forecast and renewables in the model.

There are some studies that discuss how to model load and renewable uncertainties in distribution network planning models. In order to incorporate the DG reactive capability in distribution planning, a combined PSO and ordinal optimization is proposed considering load and renewable uncertainties, exploiting sub-optimization at each system's state [7]. Moreover, an interior-point-method-embedded discrete GA is employed to solve MSDEP taking into account uncertainties associated with renewable energy generation and price-responsiveness of customers but not considering load forecast uncertainty [9]. Furthermore, to find the optimal level of renewable DGs and plug-in electric vehicle integration considering uncertainties, a method based on non-dominated sorting genetic algorithm is proposed [10]. Moreover, GA-based multi-stage distribution planning including DGs, rewiring, and network reconfiguration is proposed in [11] based on one forward and one backward planning. This work is extended to include DR in MSDEP as well [21]. In addition, a hedging algorithm to impose implementability of scenarios regarding load uncertainty in the optimization process is presented in [16]. A modified data envelopment analysis is utilized to evaluate the uncertainties regarding the location of loads after planning a distribution network for different scenarios [17]. A hybrid possibilistic–probabilistic DG and load impact on electric loss in distribution network is proposed [22]. This work is expanded to find the optimal place for DGs using a fuzzy-based approach [18]. Furthermore, a planning approach is developed to examine different air-pollutant management policies considering uncertainties using fuzzy sets [19]. In addition, a stochastic two-stage multi-period mixed-integer linear programming is proposed to minimize renewable and investment cost as well as operation and maintenance cost in distribution networks [20]. However, various types of NSs for network augmentation combined with NNSs deployment integrated with an efficient forward/backward algorithm, proposed in this paper, are not considered in these papers.

Based on AS/NZS ISO 31000 standard, the process of risk management includes establishing the context, risk assessment, and risk treatment [23]. Risk assessment involves risk identification, analysis, and evaluation. Risk treatment involves selecting one or more options for modifying risks and implementing those options [23]. According to our knowledge, there are no studies on how to treat the risk associated with the load and renewable uncertainties except in [15] and [6]. In [15], a MSDEP approach is proposed by taking into account the load forecast uncertainties in the planning process using a "multiple scenario approach". In this study, some expansion plans are built for a possible load forecast scenarios and a "reduced risk" short range plan is then created based on the high need investments required in a large number of scenarios. The risk-managed plan in that study is a short-term investment plan that describes what type of network investments in short-term will be able to meet the forecasted demand in a large number of scenarios. However, in [15], NNSs, which have been identified as a promising option, are not considered for treating the risks. In [6], the optimization of DGs' characteristics for distribution investment deferral is presented considering the variability of net present value (NPV) as a measure of risk using Monte Carlo simulations. However, this approach is very time-consuming for large-scale networks and the method can be applied for a relatively smaller size networks as: it considers MSDEP in a single model without decomposition; uncertainties are modeled by scenario analysis using Monte Carlo modeling which is very time-consuming; and only DGs are used to manage risk. However, our proposed model in this paper is applicable for large-scale networks as an efficient forward-backward decomposition technique along with the concept of probability of exceedance (POE) instead of Monte Carlo is used with integration of DR in addition to ESS/DG as a promising NNS.

In this context, a risk-managed approach for MSDEP is developed in this paper to enable utilities to plan their networks at a lower long-term cost and treat the risk of load and renewable uncertainty through customer engagement in DR and temporary ESS/DG. This approach also takes into account the uncertainty associated with DR in MSDEP. Therefore, the main aim of this paper is to develop a tool for MSDEP to examine whether it is cost-effective to manage the risk associated with uncertainties of load and renewable generation using temporary NNSs rather than investing on a high level of a network capacity to meet these uncertainties. Along with this, the proposed MSDEP procedure provides a solution to how to treat the risks at each year over planning years. The proposed risk-managed model has the following main contributions:

– Propose an efficient solution approach to developing least-cost long-term network expansion plans for large real-sized distribution networks considering various types of NSs (distribution transformers, conductors, voltage regulators, reactive power compensators, and fixed ESS) and NNSs (DR and temporary ESS/DG) in the presence of renewables and load uncertainties.
– Present an approach for treating the risks associated with uncertainties of load and renewable generation.
– Present a lumped model of incorporating of NNSs in the model to treat the consequences of risk associated with uncertainties.

This paper is organized as follows. The next Section gives the concept of risk-managed planning and detailed description of uncertainty modeling of renewables and loads. This is followed by Section III which describes the modeling of NNSs. The problem formulation of MSDEP is presented in Section IV. The Section V proposes an efficient solution approach for MSDEP. The simulation results are provided in Section VI. Finally, Section VII presents the relevant conclusions.

II. Risk-managed Planning Concept

Existing planning approach is to design the network for given demand forecast with a high reserve margin to take into account uncertainties of the forecasts. As shown in Fig. 1, traditional planning will result in building network capacity up to level given by "▲" line. This conservative planning approach is not the solution for the future active network as it results in building extra network capacity to tackle increased uncertainties. A new flexible risk-managed network planning tool is proposed in this study to replace this conservative inflexible planning approach. The philosophy of the proposed approach is to find the "optimal level of demand" (shown in Fig. 1 as "■" line) at each year at which the network should be upgraded using NSs (named *DSNS*, stands for demand supplied by NSs), while, procuring temporary NNSs (DR and temporary ESS/DG), see Section III, to treat the risk of exceeding demand above this level. This optimal level of demand is determined in our model by finding the bounds of trade-off between savings due to the postponement of investment of NSs versus the cost of temporary NNSs. Therefore, the DSNS will be a decision variable in our model in contrast to the traditional planning models. The proposed planning process, See Section V, will evaluate whether it is cost-effective to treat the risk associated with uncertainties of load and renewable generation using temporary NNSs rather than investing on a high level of a network capacity to meet these uncertainties. As shown in Fig. 1, the NNSs will defer the extra network investments while reducing the total network expansion cost, which is the sum of NS cost and the cost of procuring NNSs. For example, as seen in Fig. 1, the total network capacity of 3MVA, i.e. 2×1MVA and 2×0.5MVA distribution transformers, is required to be installed at 2016 based on the traditional planning approach. However, based on the proposed risk-managed approach, this 3MVA network augmentation is deferred to 2019, 2020, 2022, and 2023. As seen, each 1MVA distribution transformer is installed at 2019 and 2020 and the installation of each 0.5MVA distribution transformer is planned on 2022 and 2023. During this period, 2016 to 2023, the extra load over the capacity of the network is supplied by NNSs. In this example, at the year 2018 and 2022, NNSs supply about 1 MVA and 1.5 MVA of the load, respectively.

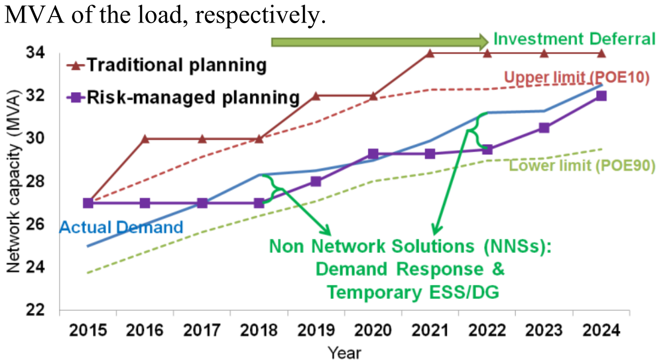

Fig. 1. Risk-managed planning concept.

A) Uncertainty Modeling

Solar PV is the most popular renewable energy source connected to distribution networks in Australia. A high penetration of solar can have positive and negative impacts on the network depending on the network structure, demand profile, and PV electricity generation profile. Therefore, the networks should be designed to handle the predicted level of solar PV deployment. This Section describes how to incorporate solar PV and load uncertainties in our model from the forecasted demand profile and the generation profile from the solar PV made available in [24]. All PV generation is considered as active power injection in this model, however, this model can be extended to include the reactive capability of PV interfaces [7]. At each node, the yearly profiles are considered as the mean values of forecasts whose standard deviations (SDs) at each time window, i.e. half an hour, is defined as uncertainty levels. The uncertainty levels for demand and PV demands forecasts could be, for example, 5% and 10%, respectively. Therefore, using mean and SD values, 50 profiles for demand and PV are generated for each node based on a Gaussian PDF at each time window. The difference between demand and PV profiles at each time is defined as an *effective time series load profile* for each node. Using the *effective time series load profiles*, the corresponding effective load duration curves (LDCs) are obtained. Fig. 2 shows 50 effective LDCs at a node for 5% uncertainty level (error) assigned to both demand and PV forecast, generated from the Gaussian PDF. The SD of a variable is calculated from the corresponding Gaussian-distributed error as $\sigma = \varepsilon \times \mu/300$ [25], where σ, ε, and μ are the SD, the percentage error, and the mean value of that variable, respectively.

The effective LDCs for each node can be used to find the multivariate Gaussian mixture model (GMM) of each load point as in [7]. However, as explained in [26], the load points can be modeled as a single equivalent Gaussian at different load levels of LDC. This is because in each selected load level of the LDC, the PDF of demand is similar to one equivalent

Gaussian PDF [27]. For example, five load levels are shown in Fig. 2. Therefore, the statistical characteristics of the active and reactive power of the load points are obtained for each load level of LDC. The reactive power profile is obtained using active power profile and power factors which are fixed for high and low demand, namely, 0.88 and 0.82, respectively, based on the sample measurement in a real network [25]. Therefore, The mean and SD of the Gaussian PDF for kth load level at ith node are $\mu_{i,k}$ and $\sigma_{i,k}$, respectively. The details of steps of the procedure for finding the load statistical characteristics are revealed in [26]. It is important to note that LDCs for different nodes are treated using the same time series to include correlation between load points. The whole procedure can also be extended to consider GMM as future study. In order to calculate probabilistic characteristics of voltage and current at each node at each year, this probabilistic effective load model is used as described in Section IV-D.

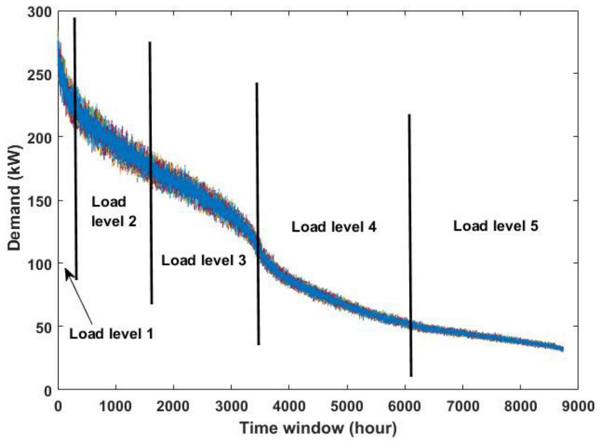

Fig. 2. Effective LDCs at a node for the same uncertainty level of 5% for both demand and PV forecast with determined 5 load levels.

- *Uncertainty of load forecast*

A list of at least 30 techniques for risk assessment and their applicability comparison are provided in Annex A and B of ANSI Z690.3-2011 standard [28]. These risk assessments techniques are categorized into three main types: rule based, probabilistic based, and judgment based [29]. Rule based assessments are usually based on a set of standards or checklists to check the system compliance such as structured what-if technique (SWIFT) and checklist technique. While probabilistic based and judgment based assessments analyze probabilities and impacts for each undesired event using tools such as Markov and Monte Carlo analysis. The difference between these two types is that for probabilistic based assessment, only empirical data is used to estimate the probability while the subjective interpretation of the expert is used for judgment based assessments as the probability [29]. Since, in this paper, empirical data is utilized for the probability estimation, the risk modeling of the proposed risk-managed approach in this paper falls into the category of probabilistic based risk assessment. The probabilistic risk assessment is a comprehensive technique to evaluate the risk in complex systems, which employs some other tools as well [30]. Within this category, fundamentally, the risk associated with an event is defined as its consequence weighted by its likelihood as [31]: Risk value = Probability × Impact. Therefore, in a risk assessment process, two main parameters should be determined, which are the probability and the impact of all events. Two common techniques for the probability calculations are event tree analysis (ETA) and fault tree analysis (FTA), which are, respectively, bottom-up and top-down analysis [30]. In this paper, a similar approach to FTA is used to calculate the cumulative distribution functions (CDF) of occurrence of events by processing the data of load and renewable generation and their uncertainties over the planning period for the top node of the network, as described in this Section. Then, loading characteristics of each node in the network are determined based on each corresponding effective LDCs, as will be described in this Section. In addition, to take into account the risk associated with equipment failure, the reliability cost (cost of SAIFI and SAIDI) is included in the objective function, as explained in Section IV-C. The approach for these reliability indices calculations is similar to ETA's approach. Moreover, for the impact analysis, the expected unit cost for treating the consequence of each event is calculated as the risk-managed cost, as detailed in Section IV-A.

Using effective LDCs over planning years, described in this Section, the CDF of the effective load at each node is obtained. Then, in this paper, the probability of exceedance (POE) extracted from CDF of peak load, as the main driver of capacity augmentation in distribution networks, at each node is utilized to model the uncertainties of the peak load forecast. It should be noted that the time window series for LDC of the main source in a distribution network is considered as the reference for all LDCs at other nodes to be evaluated based on this reference. The CDF of effective load using effective LDCs over ten years with the average growth of 2% for a node is shown in Fig. 3. The term POEx means the level of effective load that has $x\%$ probability of being exceeded by the maximum effective load recorded in any year based on the knowledge of the current year. Therefore, the POE10 is the level of load such that the annual load will exceed this level on average once every ten years. It is important to note that the POE10 is not equal to the demand that the load is bigger than it 10% of the times in a year. Therefore, the probability of occurrence of maximum effective load (D) exceeding POEx is $x\%$, that is:

$$P(D > POEx) = 1 - F_D(POEx) = x\% \qquad (1)$$

where $P(A)$ is the probability of event A and F_D is the CDF of D. Therefore, the probability of occurrence of D within ith level of load, namely, p_i , is expressed as:

$$p_i = P(POEx_i < D \leq POEx_{i+1}) = F_D(POEx_i) - F_D(POEx_{i+1}) = x_{i+1}\% - x_i\% \qquad (2)$$

These load levels, POEx, are examined during the proposed planning process, see Section V, in this paper to find a cost-effective solution to treat the risk associated with load exceedance due to demand and renewable uncertainty.

It is important to note that electric distribution companies in Queensland, Australia do not incur any cost of solar PV installation (feed-in tariff or incentives) [32] and hence in our model, the uncertainty of solar PV locations is not considered. However, the proposed approach in this paper can be extended to consider this type of uncertainty as well.

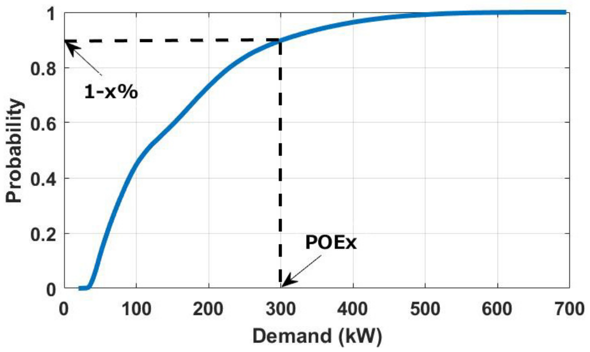

Fig. 3. The CDF of effective load over 10 years of planning for a node.

III. Modeling of Non-network Solutions

The NNSs are becoming an integral part of network planning, and hence, MSDEP models need to be enhanced to incorporate short-term NNSs in long-term planning. In an ideal case, individual NNSs (such as DR, ESS, and DG) should be considered as decision variables in the model, but using this ideal approach to a real size network would increase the problem size significantly. Therefore, in this Section, we propose a compact lumped model to represent all NNSs using one decision variable in MSDEP model. As described, one of the decision variables in the proposed model, in addition to the variables of the individual NSs, is the DSNS. Therefore, this decision variable indirectly gives the level of demand that needs to be supplied by the NNSs. The input of the compact model, presented here, is the required power supplied by NNS and the outputs of the proposed compact model are the nominal power and energy of each NNS for supplying this level of demand and their associated hours and costs. The prepossessing data for the optimum contribution of NNSs for each level of demand and their associated costs are carried out before starting the planning process. These pre-possessing data are used to find the best combination of NNSs for each particle as described in Section V.

Since different levels of peak load reduction (or peak shaving) are associated with different duration depending on the load profiles, the combination of NNSs that can supply different levels of demand reduction will vary with peakiness of the load profile as shown in Fig. 4. Since NNSs are characterized by power (kVA) ratings and energy ratings (kWh) or duration, here, both characteristics are obtained. Some NNSs are more appropriate for supplying a very peaky demand shape with a high level of kVA for a shorter duration than others, which are appropriate for supplying lower level of kVA for a longer duration. Therefore, the best combination of NNSs for supplying different level of peak demand can vary depending on the characteristics of NNSs (kVA rating, kWh rating, and cost) and the shape of load profile.

The proposed compact lumped NNS model is developed in two steps; 1) pre-processing the NNSs effect for different levels of peak demand reduction using the *effective time series load profile* obtained in the Section II, 2) calculating power and energy rating of each type of NNSs from the required kVA and duration considering the characteristics of NNSs.

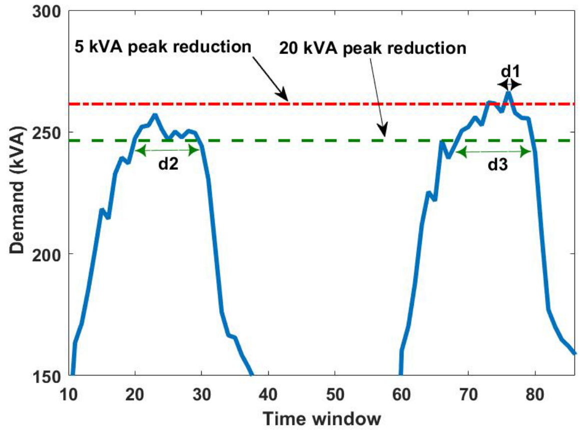

Fig. 4. Different durations associated with different peak load reduction

In the first step of the lumped NNS model, the following steps are taken to find the duration of NNSs necessary for different levels of peak shaving:

1) Retrieve the effective time series load profile at a node from Section II.
2) Select a "peak shaving level (kVA)" at this node for example 5 and 20 kVA as seen in Fig. 4.
3) Find the periods in which the profile exceeds the value of "peak demand over the year – peak shaving level" and calculate the associated duration. For example, d1 for 5 kVA and d2 and d3 for 20 kVA peak reduction in Fig. 4. Since the periods usually occurred daily, it is assumed that these periods are independent. For example, ESS is charged completely and ready to use in the next day after discharging during a day.
4) Obtain the maximum duration of the periods in step 3, which is "maximum continuous hours" of NNS over a year. For example, d1 for 5 kVA and d3 (d3> d2) for 20 kVA peak reduction in Fig. 4.

Fig. 5 shows the maximum continuous hours of NNS deployment versus different peak load shaving (blue line) extracted from an effective time series load profile for a node obtained in Section II.

For the second step of the lumped model for NNS, it is assumed that the incremental cost of DR is smaller than that for temporary ESS/DG [33]. Therefore, the strategy of utilization of NNSs, in this paper, is based on the maximum usage of DR then addressing excess duration (hours) and/or excess demand using temporary ESS/DG. In this paper, DR is considered as consumers' demand deferral which is capped by a maximum demand and maximum hours (red lines). In order to forecast DR uncertainties, advanced and complicated economic and social analyses are necessary [34]. Here, a truncated Gaussian distribution is utilized to model the uncertainty associated with the flexible part of the load or responsiveness of the load [9]. Therefore, the PDFs of available kVA, kVA_{DR}^{ava}, and duration, H_{DR}^{ava}, of DR are modeled as follows:

$$H_{DR}^{ava} \sim Gaussian\left(\mu_{H_{DR}^{ava}}, \sigma_{H_{DR}^{ava}}\right), H_{DR}^{min} \le H_{DR}^{ava} \le H_{DR}^{max}$$
$$kVA_{DR}^{ava} \sim Gaussian\left(\mu_{kVA_{DR}^{ava}}, \sigma_{kVA_{DR}^{ava}}\right),$$
$$kVA_{DR}^{min} \le kVA_{DR}^{ava} \le kVA_{DR}^{max} \quad (3)$$

where "~" stands for "is distributed as"; $\mu_{H_{DR}^{ava}}$ and $\sigma_{H_{DR}^{ava}}$ are the mean and SD of duration of DR; $\mu_{kVA_{DR}^{ava}}$ and $\sigma_{kVA_{DR}^{ava}}$ are the mean and SD of kVA of DR; H_{DR}^{min}, H_{DR}^{max}, kVA_{DR}^{min}, and kVA_{DR}^{max} are minimum and maximum of duration and kVA of DR, respectively.

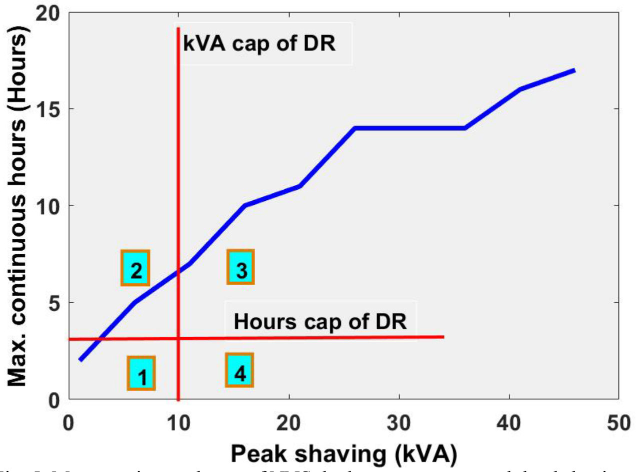

Fig. 5. Max. continuous hours of NNS deployment versus peak load shaving.

Therefore, the contributions of DR and temporary ESS/DG for a required $kVA_{req}^{y,i}$ reduction at the year y at ith level of load at a specific node (for simplicity, the node index is not appeared.) are calculated through lumped model as follows:

1. Find the power contribution of each NNS at the year y at ith load level where the jth level of available kVA for DR is $kVA_{DR}^{ava,j}$ as follows.

$$kVA_{DR}^{y,i,j} = \min(kVA_{req}^{y,i,j}, kVA_{DR}^{ava,j})$$
$$kVA_{ESS/DG}^{y,i,j} = kVA_{req}^{y,i,j} - kVA_{DR}^{y,i,j} \quad (4)$$

The index j is added to other parameters as well to represent the variable at the jth level of DR.

2. Find the required hour of NNS utilization, namely, $H_{req}^{y,i}$, at the year y at the ith level of load using Fig. 5. Therefore, the hours of utilization for each NNS are obtained as follows where the jth level of available duration for DR is $H_{DR}^{ava,j}$. Here, the index j also shows the parameters represented at the jth level of DR.

$$H_{DR}^{y,i,j} = \min(H_{req}^{y,i,j}, H_{DR}^{ava,j})$$
$$H_{ESS/DG}^{y,i,j} = H_{req}^{y,i,j} - H_{DR}^{y,i,j} \quad (5)$$

3. Calculate expected value of kVA and duration after adjusting the durations and kVAs of temp. ESS/DG as:

$$if\,(kVA_{ESS/DG}^{y,i,j} > 0 \; and \; H_{ESS/DG}^{y,i,j} = 0): \; H_{ESS/DG}^{y,i,j} = H_{DR}^{y,i,j}$$
$$if\,(kVA_{ESS/DG}^{y,i,j} = 0 \; and \; H_{ESS/DG}^{y,i,j} > 0): kVA_{ESS/DG}^{y,i,j} = kVA_{DR}^{y,i,j} \quad (6)$$

Then, expected values are calculated as follows where $E(x^j)$ is the expected value of variable x^j.

$$kVA_{DR}^{y,i} = E(kVA_{DR}^{y,i,j}), H_{DR}^{y,i} = E(H_{DR}^{y,i,j})$$
$$kVA_{ESS/DG}^{y,i} = E(kVA_{ESS/DG}^{y,i,j}), H_{ESS/DG}^{y,i,j} = E(H_{ESS/DG}^{y,i,j}) \quad (7)$$

4. Find energy contribution of each NNS at the year y at ith level of load as

$$kWh_{DR}^{y,i} = kVA_{DR}^{y,i} \times H_{DR}^{y,i} \times pf^{y,i}$$
$$kWh_{ESS/DG}^{y,i} = kVA_{ESS/DG}^{y,i} \times H_{ESS/DG}^{y,i} \times pf^{y,i} \quad (8)$$

where $pf^{y,i}$ is power factor of effective load at the year y at ith level of load.

For example, if during the planning procedure, see Section V, peak shaving of 3 kVA is assigned to NNSs, Fig. 5 implies that the associated duration for this level of reduction is 4 hours, which falls in quadrant#1. Therefore, DR can respond to and address this level/duration of NNA. In this cases, the casting of DR is also applied for NNA costing.

- *Costing of NNSs*

The costing of nth type of NNS at ith level of load at year y, namely $C_{NNS,n}^{y,i}$, in general, is expressed as:

$$C_{NNS,n}^{y,i}(kWh_n^{y,i}, kVA_n^{y,i}) = k_{1,n} + k_{2,n} \times kWh_n^{y,i} + k_{3,n} \times kVA_n^{y,i} \quad (9)$$

where $kWh_n^{y,i}$ is the maximum continuous kWh and $kVA_n^{y,i}$ is the peak of power can be delivered by nth NNS over ith level of load at year y. The definitions of three constants parameters; $k_{1,n}$, $k_{2,n}$, and $k_{3,n}$ are different for different types of NNS and are described in TABLE I. Therefore, the total cost of NNSs for the required $kWh^{y,i}$ and $kVA^{y,i}$ at the year y at ith level of load is as:

$$C_{NNS}^{y,i}(kWh^{y,i}, kVA^{y,i}) = C_{NNS,DR}^{y,i}(kWh_{DR}^{y,i}, kVA_{DR}^{y,i}) + C_{NNS,ESS/DG}^{y,i}(kWh_{ESS/DG}^{y,i}, kVA_{ESS/DG}^{y,i}) \quad (10)$$

TABLE I
THE DEFINITION OF COSTING PARAMETERS FOR NNSS

Type of NNS	k_1	k_2 (\$/kWh)	k_3 (\$/kW)
Temporary ESS/DG	Preparation cost	Battery/Delivered energy cost	Inverter/DG purchased cost
DR	Availability cost [35]	Deferred energy cost [36]	Deferred demand cost [36], [37]

IV. Problem Formulation

The risk is "an effect of uncertainty on objectives" [23] in which an effect is "a deviation from the expected" [23]. Based on this definition, the risk here is the effect of the customer load, exceeding a planned level at each year, on a distribution network. The consequence of this event is the violation of objectives of electric network planning, which are technical constraints violation and unacceptable reliability of system mainly due to lack of network capacity, which appears as energy not served or load shedding. In order to treat [23] such risks, NNSs and NSs are utilized at a minimum long-term cost to meet projected demand in the presence of load forecast and renewable generation uncertainties, while meeting the system technical constraints. Reliability indices are also included in the objective of the planning as an equivalent cost of reliability to reflect well customer damage costs. Therefore, in this study, the objective function is the total probabilistic cost of NNSs and NSs over planning years, which is formulated as a mixed integer nonlinear programming problem as:

$$Min.of\ \sum_{y=1}^{H} C_{Prob}^{y} = \sum_{y=1}^{H} C_{Prob,NNS}^{y} + \sum_{y=1}^{H} C_{Prob,NS}^{y} + \sum_{y=1}^{H} C_{reliability}^{y}$$

$$subject\ to: \begin{cases} P\left(0.95 \le \left|v_i^y\right| \le 1.05\right) \ge 0.95 \\ P\left(\left|I_i^y\right| \le 1.1\right) \ge 0.95\ , \quad \begin{matrix} i = 1 \dots n \\ y = 1 \dots H \end{matrix} \end{cases} \quad (11)$$

where C_{Prob}^{y}, $C_{Prob,NNS}^{y}$, $C_{Prob,NS}^{y}$, and $C_{reliability}^{y}$ are the NPV of the total, NNS, NS, probabilistic costs and reliability cost, at year y, respectively, H is the horizon year of the network planning, v_i^y and I_i^y are the voltage at ith bus and current of ith branch at year y, respectively, n is the number of buses, and $P(A)$ is the probability of event A.

A. NNS probabilistic costs, $C_{Prob,NNS}^{y}$

Since the consequences of the risk associated with load and renewable uncertainty are mainly treated using NNSs, the expected value of NPV of NNSs at each year is defined as the risk-managed cost (RMC) or C_{RMC}^{y} for year y.

Therefore, total RMC over planning years is formulated as:

$$\sum_{y=1}^{H} C_{Prob,NNS}^{y} = \sum_{y=1}^{H} C_{RMC}^{y} = \sum_{y=1}^{H}\sum_{i=1}^{m} C_{NNS}^{y,i}\left(kWh^{y,i}, kVA^{y,i}\right) \times p_i = \sum_{y=1}^{H}\sum_{i=1}^{m} C_{NNS}^{y,i}\left(kWh^{y,i}, kVA^{y,i}\right) \times (x_{i+1}\% - x_i\%) \quad (12)$$

where p_i is the probability of demand being within ith level which is between $POEx_i$ and $POEx_{i+1}$, m is the number of load levels, and C_{RMC}^{y} is the risk-managed cost at year y. As seen, $C_{NNS}^{y,i}\left(kWh^{y,i}, kVA^{y,i}\right)$ depends on ith level of load and required $kWh^{y,i}$ and $kVA^{y,i}$ as described in (10), Section III. The different levels of POEx are usually provided by the utilities or market operators [38].

B. NS probabilistic costs, $C_{Prob,NS}^{y}$

The network solutions in this paper include distribution transformers, conductors, voltage regulators, capacitors, and fixed ESS. Since the network solutions are upgraded for a level of loading, DSNS, as previously mentioned in Section II, these upgrades are the same for different load levels. Therefore, the total probabilistic cost of NSs is:

$$\sum_{y=1}^{H} C_{Prob,NS}^{y} = \sum_{y=1}^{H}\sum_{i=1}^{m} C_{NS}^{y,i} \times p_i = \sum_{y=1}^{H} C_{NS}^{y} = \sum_{y=1}^{H}\left\{C_{NS,fix}^{y} + C_{NS,var}^{y} + C_{O\&M}^{y} - C_{salvage}^{y}\right\} \quad (13)$$

where $C_{NS,fix}^{y}$ and $C_{NS,var}^{y}$ are NPV of fixed and variable investment cost of network solutions at year y, respectively, as provided in [4], [8], [39]. $C_{O\&M}^{y}$ is the NPV of operation and maintenance (O&M) cost and $C_{salvage}^{y}$ is the salvage value of $C_{NS,var}^{y}$ based on the straight line calculation [40]. O&M cost includes the fixed O&M cost, the costs of energy loss and power loss as follows.

$$C_{O\&M}^{y} = C_{O\&M,NS}^{y} + E_{Loss}^{y} \times C_{ELoss}^{y} + P_{Loss}^{y} \times C_{PLoss}^{y} \quad (14)$$

where $C_{O\&M,NS}^{y}$ is the fixed O&M cost of the NSs at year y, which is calculated as a fixed percentage of variable NS investment ($C_{NS,var}^{y}$), i.e. 2%, at the same year in this model. E_{Loss}^{y} and P_{Loss}^{y} are total expected energy loss and power loss at year y, respectively, which are calculated for different level of loading at each year. C_{ELoss}^{y} and C_{PLoss}^{y} are cost of energy loss and power loss at year y, respectively. The details of the formulations are provided in [8] [39].

C. Reliability cost, $C_{reliability}^{y}$

The reliability cost is calculated as an equivalent cost of system average interruption duration index (SAIDI) and system average interruption frequency index (SAIFI) as

$$\sum_{y=1}^{H} C_{reliability}^{y} = \sum_{y=1}^{H} SAIDI^{y} \times C_{SAIDI}^{y} + SAIFI^{y} \times C_{SAIFI}^{y} \quad (15)$$

where $SAIDI^{y}$, and $SAIFI^{y}$ are the expected SAIDI and SAIFI across different level of load calculated at year y, respectively. C_{SAIDI}^{y}, and C_{SAIFI}^{y} are the value of customer reliability (VCR) [41] for SAIDI per customer-minute and SAIFI per failure-customer at year y, respectively. For evaluation of network reliability using these indices, network voltage and thermal limits are also included when the network relies on the cross-connects [42]. In this paper, only existing cross-connects are considered and, the planning, design, and upgrade of cross-connects are included as future works. Therefore, total cost of reliability, here, takes into account the cost associated with loss of supply due to technical constraints.

D. Constraints

As seen in (11), there are two constraints for the given demand forecast; a) the voltage magnitude at each node at each year should be within the specific limits, and b) the current flowing through each branch and network equipment at each year should not exceed the maximum capacity. The voltage magnitude of nodes and thermal capacity of branches and network equipment are presented in a probabilistic manner. For example, the probability of voltage magnitude being within standard limit should be higher than 95%. In order to obtain statistical measures for electrical parameters, in this paper, the fast and efficient probabilistic distribution state estimation (DSE) algorithm proposed in [26] is fitted to calculate statistical parameters of bus voltages and branch currents at each year. The DSE uses the nodes' statistical parameter obtained via the process described in Section II. The feeder forecast data is considered as measurements in this DSE. Through optimization procedure, as discussed in Section V, this constraint is treated as a penalty (a large number in case of violation) in the objective function. If the accurate costing of the violations is available, these values are used as the penalty to taking into account the depth and individual consequence of violations across a network. In general, this penalty can be presented as a function of cost of violations as: $Penalty = \sum_{i=1}^{n} C_{\Delta v_i}(\Delta v_i) + \sum_{i=1}^{n-1} C_{\Delta I_i}(\Delta I_i)$, where Δv_i and ΔI_i are the magnitude of voltage and current violations at ith bus and ith branch, respectively, $C_{\Delta v_i}$ and $C_{\Delta I_i}$ are the corresponding cost functions of Δv_i and ΔI_i, respectively. In this paper, a big number is selected for both $C_{\Delta v_i}$ and $C_{\Delta I_i}$ in the case of violation.

The flowchart of C_{Prob}^{y} calculation is provided in Fig. 9.

V. Solution Approach

The exact mathematical methods can only be applied to solve a MSDEP problem for small scale networks, specially due to the non-convexity of the expansion planning problem [6]. In addition, a high computational effort is required for a numerical solution, which increases exponentially as the size of the problem increases (the curse of dimensionality) [43]. Therefore, in this paper, a heuristic optimization approach (Section V-B) is proposed to solve the MSDEP problem for real-sized networks. In large-scale MSDEP problems, even with heuristic optimization, achieving good solutions remains a time-consuming operation. One of the main factors for this, besides the large dimension of the network, is the time dynamic nature of the problem. Therefore, in most of the cases, solving the full dynamic programming algorithm is not feasible [43]. Due to this reason, in this paper, a forward-backward pseudo-dynamic algorithm (Section V-A) is used to decompose the multistage problem into a sequence of single stage problems and to solve each stage independently. Then the results for all stages are coordinated through the proposed strategy to find the optimal solution for the multi-stage problem. Briefly, the proposed solution approach consists of three steps; 1) decomposition of the MSDEP problem into single-stage problems, 2) solving single stage problems using a heuristic optimization approach, and 3) applying forward-backward strategy to coordinate the single-stage solutions to find the optimal plan.

A. Decomposition of MSDEP using the forward-backward approach

The efficient forward-backward approach developed in [4] is used for multi-stage planning. In this proposed approach, the multi-stage (or multi-year) planning problem is first decomposed into single-stage (or single-year) problems. By considering a year within planning horizon as "Reference Year" (Ref. Year), the optimal plan is developed to meet the forecast demand of this Ref. Year, as shown in Fig. 6. To determine the subset of investments among this plan, which should be implemented in the years before the Ref. Year, the backward planning exercise is carried out. Then, the forward-filling approach is used from the Ref. Year to the last year of the planning years to determine investments for the remaining years. All possible forward-backward multi-planning scenarios that start from different Ref. Year are compared to find the best expansion plan. The flowchart of the proposed forward-backward approach is presented in Fig. 6. H in this figure represents the horizon year. Possible multi-year planning scenarios include forward fill-in from the first year to the final year, backward pull-out from the last year to the first year, and from each intermediate year backward pull-out planning until the first year and forward fill-in planning to the last year. This forward-backward planning approach gives good solutions to large MSDEP problems with acceptable accuracy and manageable computing time as the optimization is carried out for the series of single stage problems which involve comparatively smaller search space avoiding the trapping in local minima.

B. Modified particle swarm optimization (MPSO)

Due to the nature of PSO as a heuristic approach proven to be capable of handling highly non-linear and mixed integer problems [43-47], in this paper, PSO is used to solve single stage distribution expansion planning problems. The stability and convergence of PSO in a multidimensional complex space is proved in [46]. This reference also provides a set of coefficients to control the system's convergence tendencies, i.e., exploration versus exploitation propensities. In addition, the performance of the classical and PSO-based optimization is studied in [47]. The results show that although the final solution from some classical approaches such as Benders decomposition is the same as a PSO-based algorithm, the computational time for PSO is 31 times faster than Benders decomposition [47]. Furthermore, the efficiency of the PSO-based algorithm is 19% better compared to classical linear programming, as investigated in [48]. Moreover, the evaluation of the employed MPSO in this paper against three well-known heuristic methods, called original PSO, GA, and SA for distribution planning shows the better accuracy and robustness of proposed MPSO [49].

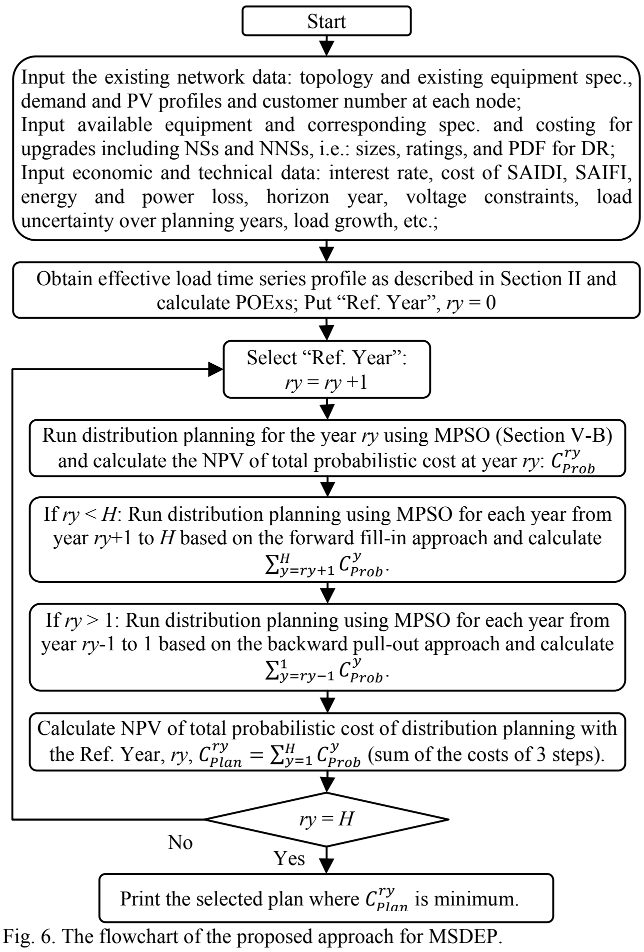

Fig. 6. The flowchart of the proposed approach for MSDEP.

In order to improve the accuracy of the solution, a modified version of PSO (MPSO) is proposed by adding the idea of mutation from the genetic algorithm (GA) as in [45], [50] into standard PSO particle update rules. In addition, the constriction factor approach for PSO is applied, here, because it has a better performance compared to the inertia weight approach [50]. The initialization process, locating the individual best particle and global best particle, and updating the velocity and particles until convergence are explained in details in [5]. For example, velocity and position update at iteration k is as follows:

$$V_i^{k+1} = \gamma \times \left(V_i^k + 0.5 \times \psi_{max} \times rand \times \left(P_{best_i} - X_i^k\right) + 0.5 \times \psi_{max} \times rand \times \left(G_{best} - X_i^k\right)\right)$$

$$X_i^{k+1} = X_i^k + V_i^{k+1} \quad (16)$$

where V_i^k and X_i^k are velocity and position of ith particle at iteration k, respectively; γ is the constriction factor coefficient; P_{best_i} is the best value of ith particle so far; G_{best} is the best value among P_{best_i}s so far; and $rand$ is a random number generator uniformly distributed between 0 and 1. The flowchart of MPSO is presented in Fig. 7.

As presented in Fig. 8, the decision variables in each particle of MPSO for single stage planning include the location and tap setting of voltage regulators (VRs), the location and the size of reactive power compensators such as capacitors, the location and the size of fixed ESS, the number of conductor upgrades, and the level of demand supplied by the NSs (DSNS index). DSNS index is a number between 10 and 90 (in the step of 10) represents the level of demand for POE10 and POE90, respectively. DSNS index gives the POEx for which the network should be upgraded using NSs. The optimal combination of NNSs that should be procured for meeting the demand exceeding this POEx level and their associated costs are then obtained based on the model described in Section III. Finally, the total probabilistic cost of each particle, C_{Prob}^y, is calculated using the costs of NSs, NNSs and the reliability as in (11) in Section IV. Fig. 9 shows the process of calculating C_{Prob}^y for each particle during the MPSO optimization.

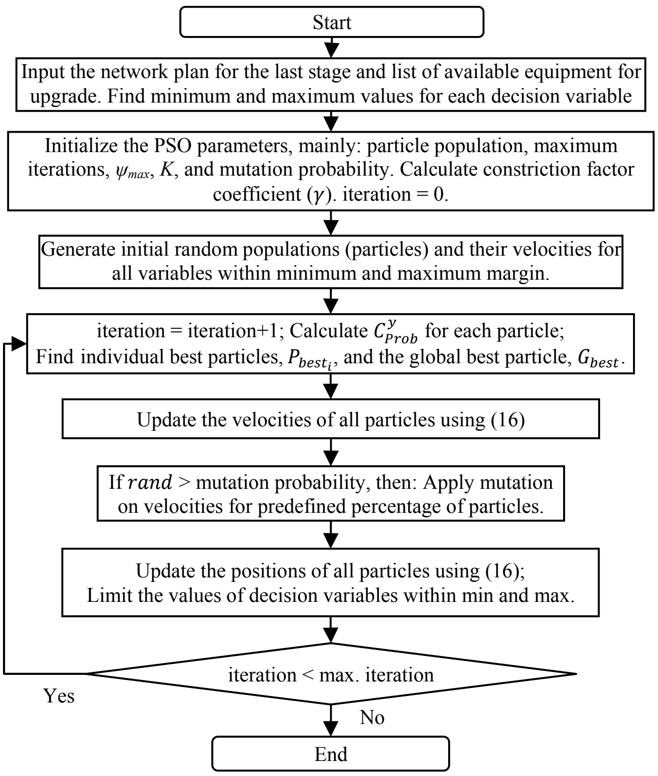

Fig. 7. MPSO flowchart

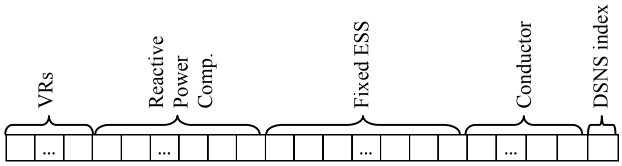

Fig. 8. Particle structure in MPSO.

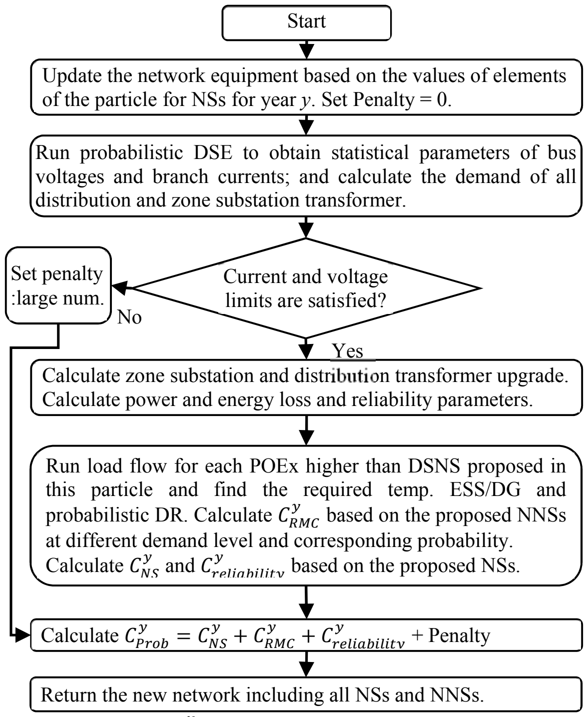

Fig. 9. The flowchart of C_{Prob}^y calculation for each particle.

VI. Simulation Results

In this paper, we illustrate the application of our proposed risked-managed approach for MSDEP for two cases as:

Case 1: IEEE 13-bus radial feeder

Case 2: realistic 747-bus distribution network: this case is for showing the capability of proposed planning approach in handling a large distribution network in reasonable time.

The same set of candidate network equipment such as overhead conductors, underground cables, pad-mounted substations, pole-mounted transformers, VR, capacitors, and fixed ESS including cost and technical characteristics as in [4] are considered in both cases. Other parameters of MSDEP, which are the same in both cases, are presented in TABLE II, obtained from the local utility, Ergon Energy Co. Ltd. The load and renewable uncertainty, which is modelled as a Gaussian distribution, at the first year is 3% and increases by 3% each year. The levels of demand forecast are represented from POE10 to POE90 in steps of 10, calculated based on the procedure described in Section II. The MPSO parameters used in the simulations are particle population=50, maximum iterations=100, ψ_{max}=4.05, K=0.99 and the mutation probability=80% and the mutation operator is applied to 10% of particle population [50]. These parameters are selected to guarantee convergence and stability of the MPSO algorithm and to provide the best solution to this specific MSDEP problem [46]. A discussion on MPSO parameter selection is presented at the end of part A in this Section.

TABLE II
THE PARAMETERS FOR MSDEP

Parameter	Value
Interest rate (%)	**5**
SAIDI cost ($/min-customer)	**1.14**
SAIFI cost ($/failure-customer)	**88**
Cost of power loss ($/kW-year)	**235**
Cost of energy loss ($/kWh)	**0.04**
Failure rate of OH/UG line. (f/km-yr)	**0.14/0.05**
Failure rate of OH/PM Trans. (f/yr)	**0.02/0.005**
Repair time OH/UG line. (min)	**180/300**
Repair time of OH/PM Trans. (min)	**900**
Switching time (min)	**60**

A. *Case 1: IEEE 13-bus radial feeder*

In this part, the results of MSDEP for IEEE 13-bus feeder, as shown in Fig. 10, are presented. The transformer sizes and their effective peak loads, as well as other network parameter, are provided in [4] and [51]. Using available data for demand and renewable generation [24], the effective time series load profiles are assigned to each node. In this network, two capacitor banks are already installed at buses 6 and 10 with a capacity of 100 and 600 kVAR, respectively. The cost of DR program is considered as \$0.382/kWh [36] whose uncertainty is modeled using the truncated Gaussian PDF with parameters presented in TABLE III for each bus. The parameters k_1, k_2, and k_3 for temporary ESS/DG costing in this study are \$100, \$0.4/kWh, and \$100/kW, respectively [52]. The load growth in this Case is 4% in average over planning years, which is applied to the number of customers at each bus as well.

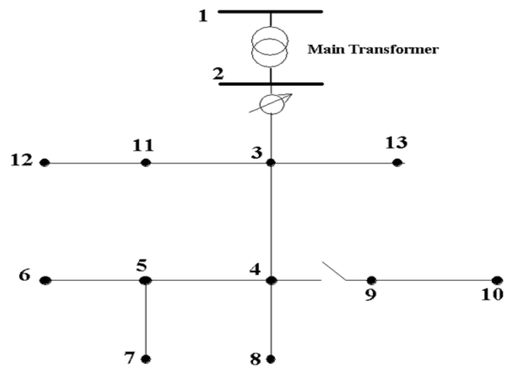

Fig. 10. IEEE 13 bus test System

TABLE III
DR statistical parameters for uncertainty modeling at each bus in Case 1.

DR parameters	Mean	SD	Min.	Max.
Power (kVA)	17.5	8.3	5	30
Duration (hours)	5	2	2	8

The least-cost network expansion plans obtained from our proposed approach for five-year planning period for different Ref. Year are presented in TABLE IV. Each network expansion plan in TABLE IV gives the optimal level of yearly POE demand ($DSNS^y$) that should be supplied by the NSs as well as the types, capacities, and timing of NSs to be added during the planning period to meet the optimal level of demand ($DSNS^y$) at minimum total cost. This table also presents the probabilistic cost of procuring the NNSs (C^y_{RMC}) to supply the demand exceeding this demand level. In other words, the risk-managed network expansion plans ensure the network capacity adequacy for an optimum level of POEx demand in each year. The optimal level of DSNS is estimated by the model so that the total probabilistic cost is the lowest for that level of demand supplied by NSs and also for the extra load over DSNS supplied by NNSs.

TABLE IV
MSDEP RESULTS FOR 5-YEAR PLANNING

Ref. Year	Upgrades	Planning years 1	2	3	4	5	Total
1	Trans. (kVA)	0	0	0	0	25	25
	Fix ESS (kVA)	0	83	639	708	700	2,130
	Cap.(kVAR)	400	450	0	0	50	900
	$DSNS^y$	POE80	POE80	POE70	POE60	POE40	-----
	$p(load^y>DSNS^y)$	90	10	30	50	70	-----
	DR (kWh)	0	977	729	518	251	2,476
	Tmp.NNS*(kW)	0	46	34	26	11	116
	SAIDI(min/no.**)	32	35	58	57	42	-----
	Power loss(kW)	201	188	161	136	122	-----
	C^y_{RMC}(k\$)	0	151	113	80	25	369
	C^y_{Prob}(k\$)	146	430	1,084	817	496	**2,973**
2	Trans. (kVA)	0	0	0	0	0	0
	Fix ESS (kVA)	0	70	683	670	685	2,108
	Cap.(kVAR)	325	475	0	25	0	825
	$DSNS^y$	POE90	POE80	POE70	POE50	POE40	-----
	$p(load^y>DSNS^y)$	80	10	40	60	70	-----
	DR (kWh)	12	999	570	351	230	2,162
	Tmp. NNS(kW)	0	48	24	17	9	98
	SAIDI (min/no.)	35	34	57	55	46	-----
	Power loss(kW)	203	187	160	139	124	-----
	C^y_{RMC}(k\$)	0.3	173	70	53	19	315.3
	C^y_{Prob}(k\$)	147	430	1,095	761	425	**2,858**
3	Trans. (kVA)	63	0	0	0	0	63
	Fix ESS (kVA)	0	210	500	640	720	2,070
	Cap.(kVAR)	325	0	0	25	50	400
	$DSNS^y$	POE90	POE80	POE70	POE50	POE40	-----
	$p(load^y>DSNS^y)$	80	20	40	60	70	-----
	DR (kWh)	11	682	528	364	228	1,812
	Tmp. NNS(kW)	0	30	24	18	13	85
	SAIDI (min/no.)	32	34	63	49	48	-----
	Power loss(kW)	203	190	169	146	129	-----
	C^y_{RMC} (k\$)	0.3	88	73	64	45	270.3
	C^y_{Prob} (k\$)	227	732	873	738	471	**3,041**
4	Trans. (kVA)	263	0	0	0	0	263
	Fix ESS (kVA)	136	266	275	636	615	1,928
	Cap.(kVAR)	0	0	0	0	175	175
	$DSNS^y$	POE90	POE80	POE70	POE50	POE40	-----
	$p(load^y>DSNS^y)$	10	30	30	60	70	-----
	DR (kWh)	553	534	819	356	257	2,518
	Tmp. NNS(kW)	16	21	36	15	10	99
	SAIDI (min/no.)	65	58	59	47	34	-----
	Power loss(kW)	190	184	175	154	132	-----
	C^y_{RMC}(k\$)	33	62	104	42	24	265
	C^y_{Prob}(k\$)	670	678	609	713	391	**3,063**
5	Trans. (kVA)	0	0	0	0	0	0
	Fix ESS (kVA)	136	268	310	533	638	1,885
	Cap.(kVAR)	0	0	0	0	0	0
	$DSNS^y$	POE90	POE80	POE70	POE50	POE40	-----
	$p(load^y>DSNS^y)$	10	30	40	60	70	-----
	DR (kWh)	546	562	561	316	239	2,224
	Tmp. NNS(kW)	16	21	24	15	13	89
	SAIDI (min/no.)	64	58	60	54	52	-----
	Power loss(kW)	190	184	175	158	141	-----
	C^y_{RMC}(k\$)	34	59	72	61	43	268
	C^y_{Prob}(k\$)	501	834	769	854	440	**3,397**

*:Tmp. NNS includes Temporary EES/DG. **:no. is the number of customers.

Another parameter reported in this table is $p(\text{load}^y > \text{DSNS}^y)$, which is the probability of load at the individual year y being exceeded from DSNS^y. While DSNS^y is calculated through processing of demand over all planning years, $p(\text{load}^y > \text{DSNS}^y)$ is the probability of exceedance at each specific year. As seen, in some cases, DSNS^ys are the same, but the associated probabilities for $p(\text{load}^y > \text{DSNS}^y)$ are different. This is because, for example, at year 2, a wide range of loading is mapped between POE80 and POE90. In order to recognize the different level of loading supplied by NSs within this interval, here, the $p(\text{load}^y > \text{POE70})$ is utilized. In addition, the expected kWh of DR during each year is reported in this table, which is calculated using the statistical parameters of DR. Moreover, for temporary ESS/DG, which is calculated probabilistically at each year, only the kW rating is presented as "Tmp.NNS" in TABLE IV. In order to compare the performance of the plan in terms of reliability, this table gives the SAIDI index at each year. In this simulation, since fixed ESS can supply part of the load in case of an outage, fixed ESS is utilized to reduce the duration of interruption and therefore considered in SAIDI calculation. As seen, utilization of fixed ESSs improves the SAIDI since the number of shed customers is reduced. However, since the number of customer increases as planning year goes by, for some years SAIDI increases despite of fixed ESS upgrades. The power loss in kW at each year is also included in TABLE IV for comparison. As shown in TABLE IV, the network expansion plan obtained from forward-backward approach for Ref. Year 2 gives the lowest total network expansion cost ($\sum C_{Prob}^y$) of \$2.858 million, which includes \$315k of RMC, which is the cost of treating the risk. It should be noted here that conductors, VRs, and zone substations are not selected by any of five expansion plans because the optimization process recognizes that they are not cost-effective NSs during the planning period. The least-cost expansion plan with "Ref. Year" 2 shows it would be cost-effective to utilize fixed ESSs and capacitors to meet the forecast demand to a certain level and procure temporary NNSs such as DR and ESS to meet the demand exceeding this level rather than investing in costly transformers. It is important to note that over use of NNSs does not lead to a more cost effective plan as seen in the plan with the "Ref Year"=4, which utilizes more DR and Temp. NNS than the optimal plan with "Ref Year"=2 uses.

As shown in Fig. 11, it is interesting to note that the total RMC during the planning period $\sum C_{RMC}^y$ decreases when Ref. Year of planning is changed from year 1 to year 5 in this Case, while total NS cost ($\sum C_{NS}^y$) increases, in average, when Ref. Year of planning is changed from year 1 to year 5. As seen, the total probabilistic cost ($\sum C_{prob}^y = \sum C_{NS}^y + \sum C_{RMC}^y$) is the lowest for the network expansion plan with the Ref. Year 2.

- *The location of upgrades at the optimal plan: Ref. Year=2*

The location and size of upgrades of NSs and NNSs for the optimal network expansion plan are presented in TABLE V. For example, new capacitors (Cap.) of 325 and 150 kVAR are installed in year 2 at buses 4 and 12, respectively. As seen, the NSs including fixed energy storage systems (ESSs) and capacitors are installed at a limited number of buses, which are bus 4, bus 6, and bus 10 to bus 13. However, the implementation of NNSs is propagated more across the network, which includes all buses except buses 1, 2, 5, and 8. As discussed, the proposed risk-managed approach finds the optimal combination of NSs and NNSs at each year. For example, for bus 4, which has the highest loading in the network [4], 640 and 600 kVA of fixed ESS are installed in years 3 and 5 respectively. In addition, 325 kVAR of the capacitor bank is provided in year 2. Regarding NNSs, DR is implemented at each year over the planning period at bus 4 with different levels, which totally shifts 579.4 kWh during contingencies in the network. Moreover, temporary ESS/DG is utilized at bus 4 on years from 2 to 5 with a total power of 57 kW. Furthermore, the augmentation of NSs and NNSs at buses located far from the main transformer is higher, for example, for buses 10, 12, and 13, as seen in TABLE V.

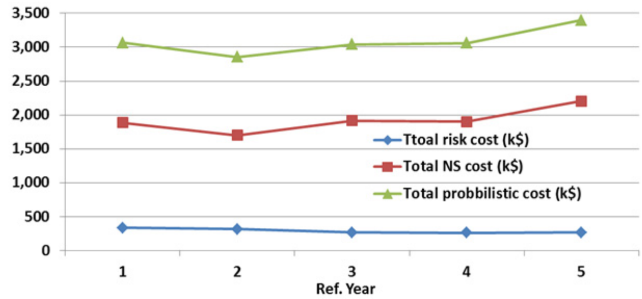

Fig. 11.The $\sum C_{NS}^y$, $\sum C_{RMC}^y$ and $\sum C_{prob}^y$ versus "Ref. Year".

TABLE V
THE LOCATION AND SIZE OF NSS AND NNSS AT THE OPTIMAL PLAN: REF. YEAR=2

Upgrades		Planning years				
		1	2	3	4	5
Fix ESS	kVA	0	70	640, 13, 30	15, 580, 75	600, 25, 60
	location	-----	10	4, 6, 12	6, 10, 12	4, 6, 13
Cap.	kVAR	325	325, 150	0	25	0
	location	13	4, 12	-----	13	-----
DR	kWh	8.4, 0.4, 0.3, 2.3, 0.3, 0.3	28, 255, 50, 26, 65, 241, 77, 96, 161	15, 153, 20, 20, 43, 125, 48, 61, 85	16, 99, 12, 12, 32, 77, 26, 27, 50	7, 64, 11, 13, 16, 16, 18, 35, 50
	location	4, 6, 9, 10, 12, 13	3, 4, 6, 7, 9, 10, 11, 12, 13	3, 4, 6, 7, 9, 10, 11, 12, 13	3, 4, 6, 7, 9, 10, 11, 12, 13	3, 4, 6, 7, 9, 10, 11, 12, 13
Tmp. NNS	kW	0	28, 10, 10	13, 5, 6	11, 3, 3	5, 4
	location	-----	4, 10, 13	4, 10, 13	4, 10, 13	4, 12

- *Voltage and currents at the optimal plan: Ref. Year=2*

The voltage magnitudes for the corresponding 95% confidence intervals for all buses over planning years for "Ref. Year"=2 is shown in Fig. 12. As seen, all bus voltages, for a 95% confidence intervals, are within ±5% of the nominal voltage. This result shows that the optimal upgrades for NSs and NNSs are identified to meet the demand while satisfying the voltage constraint in (11). As shown in Fig. 12, voltage drops to a level just above 95% of the nominal voltage at bus 2 at year 1 and it increases again at bus 3 by the voltage regulator installed in the network.

The probability of branch currents being exceeded from the nominal ratings of corresponding branches over planning years is also analyzed. The results show that only the capacity violation of the main transformer and the branch including the voltage regulator have notable values for the planning with Ref. Year = 2, as seen in TABLE VI. The thermal constraint in the problem formulation implies that with 95% confidence, each branch current of the network should be less than the rating of that corresponding branch. Therefore, as shown in TABLE VI, the probability of branches' capacity violation in this network is less than 5% which satisfies the thermal constraint over planning years.

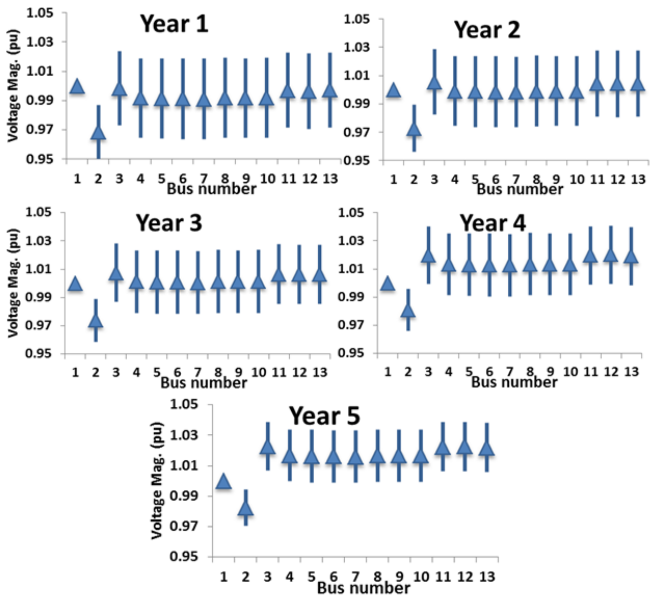

Fig. 12. Voltage magnitude and 95% confidence interval over planning years for "Ref. Year"=2.

TABLE VI
Probability percentage of capacity violation for two branches in Case 1 for optimal MSDEP.

Planning Years	*1*	*2*	*3*	*4*	*5*
Main transformer	2.27	2.24	2.25	2.25	2.26
Voltage regulator	0.31	0.31	0.32	0.36	0.39

- *The effect of uncertainty level*

As shown in the results, the level of uncertainty is one of the main parameters that determines the risk and the total cost of MSDEP. Therefore, to examine the effect of uncertainties of loads and renewables on the costs of planning, two MSDEPs are developed with different levels of uncertainty. These levels are assumed as decreasing the uncertainty level to half (1.5% in the first year and increases 1.5% each year) from the base case (3% in the first year and increases 3% each year). Another level of uncertainty is obtained by doubling the uncertainty level (6% in the first year and increases 6% each year) from the base case. Fig. 13 presents the least-cost expansion plans for different levels of uncertainty. As seen, both RMC and total cost increase with the level of uncertainty. The total probabilistic cost increases by 18% and 34% when uncertainty level is increased by 1.5% to 3% and 3% to 6%, respectively. However, RMC would increase by 45% and 217%, respectively, when uncertainty level increased by 1.5% to 3% and 3% to 6%, respectively. The share of RMC in total probabilistic cost is 12%, 13%, and 17%, respectively for uncertainty level of 1.5%, 3%, and 6%. In addition, the exploitation of NSs is increased to present a balanced plan including NNSs to cope with the uncertainties in the future years. This means that high level of uncertainties justifies the investment on high-cost NSs such as transformer in this case.

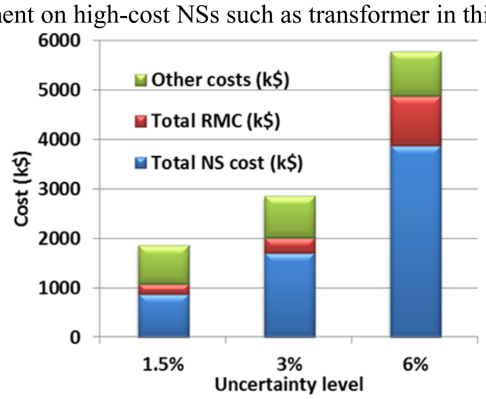

Fig. 13. The total RMC and NS cost for different levels of uncertainty.

- *The effect of DR level*

To study the influence of DR on MSDEP, different levels for DR are considered. In this simulation, three levels for the mean of DR based on ±30% of the base mean values are assumed, and the SD is kept the same as in TABLE III. Other parameters such as minimum and maximum are also modified accordingly. The optimal total and risk-managed costs for different levels of DR are presented in TABLE VII. As seen, the total probabilistic cost would increase +2.2% and decrease 2.3% where mean values for DR change +30% and −30%, respectively. As seen, the risked-managed cost increases in both cases because in case of +30%, more DR is utilized instead of NS upgrade and therefore, the associated cost is higher. In case of −30%, although the level of DR proposed by MSDEP is less than the base case, the temporary ESS/ DG increases and consequently, the total risk-managed cost is higher than the base case.

TABLE VII
The optimal total cost for different levels of DR uncertainty.

Mean of DR			**Total**	**Total**	**% of change**
Change in mean	**Power (kVA)**	**Duration (hours)**	C^{y}_{RMC}**(k$)**	C^{y}_{Prob}**(k$)**	**in total cost (%)**
-30%	10.5	3.5	422	**2,920**	**+2.2**
Base case	17.5	5	315	**2,858**	**0**
+30%	22.8	6.5	440	**2,791**	**-2.3**

- *Comparison against the traditional plan (without NNSs)*

In order to show the effectiveness of the proposed approach and the advantages compared to the traditional approach for MSDEP, the network is planned considering only NSs, not any NNSs. The uncertainty, in this case, is the same as the base case. The simulation result shows that the total necessary upgrades without NNSs cost $153k more than that with NNSs. It is important to note that this difference is only for the 13-

bus network, and this number will increase in the case of large-scale distribution networks.

- *Computational efficiency and MPSO parameter analysis*

The computational time for a 5-year MSDEP for Case 1 study based on the proposed approach in this paper is about 5 minutes in MATLAB software on Intel CORE i7-4770 PC with clock speed 3.4 GHz and 16 GB RAM. In order to show the stability of the proposed algorithm for MSDEP, the algorithm is run for 50 times for Case 1 and the mean and SD of the total probabilistic cost are obtained. In addition, the selection of MPSO parameters to achieve the best performance of the proposed approach for MSDEP is discussed. To this aim, a sensitivity analysis is carried out to evaluate the performance of the proposed approach for MSDEP with different values for MPSO parameters.

The appropriate selection of parameters is discussed in [46] to guarantee convergence and stability of the MPSO algorithm. As mentioned in Section V-B, the constriction factor approach for MPSO is applied, here, because it has a better performance compared to the inertia weight approach. Three types of constriction factors are presented in [46], however, the simple version (Type 1″) is selected in this paper, because this type requires the least number of adjusting coefficients with no increase in time or memory resources [46]. The parameter $K \in]0,1[$ is a coefficient allows control of exploration versus exploitation propensities. For the bigger value of coefficient K, particles show more exploration and limit explosion, which facilitates searching the space thoroughly before collapsing into a point. However, for smaller values of K, particles exhibit more exploitation and less exploration [46], [50]. Therefore, in order to find an optimal solution more likely and to examine the search space well, in MSDEP problem, K =0.99 is selected. ψ_{max} is another parameter showing how PSO uses the previous information as optimization progresses [46]. If ψ_{max} <4, oscillation behavior is seen in the optimization convergence. If ψ_{max} is much higher than 4, a quick convergence will occur [46]. Therefore, in this paper, ψ_{max} =4.05 is selected to avoid spiral tendency and to prevent premature convergence. About the other parameters such as particle population, maximum iterations, the mutation probability, and the percentage of the population that mutation operator applied to, namely, %mp, a sensitivity analysis is run. Various combinations of these parameters are examined and some results for the mean and SD of the total probabilistic cost are presented in TABLE VIII. In order to keep the time of simulation, approximately, constant, the product of particle population and maximum iterations is maintained fixed in this analysis.

As seen in TABLE VIII, in options 1, 2, and 7, the mean values are the same, but, the SD of option 1 is smaller than the SD of options 2 and 7. In addition, the SDs of options 1 and 5 are similar. However, the mean value of option 5 is bigger than the mean of option 1. Therefore, for MSDEP problem in this paper, the MPSO parameters in option 1 are selected. The result for option 1 presents that the SD of the solution is about 1%, showing the proposed solution in this paper is a good and reliable solver for the MSDEP. Furthermore, this sensitivity analysis is run for bigger values of ψ_{max} and smaller values of K. The results of this study also show that the outcome is not better than that for the option 1 reported in TABLE VIII. Moreover, the MSDEP problem is performed with 500 iterations for 50 runs while the other parameters are the same as for option 1. The result of this analysis shows 1.5% improvement in the mean value of MSDEP, from $2,862k to $2,818k, with the same value for SD. However, the computational time for this study is about five times, in average, higher than the time for the case with 100 iterations. This simulation demonstrates that the number of iterations selected in this paper, which is 100, is adequate considering the accuracy improvement gained and the higher computational effort and the corresponding time through increasing number of iterations.

TABLE VIII

THE RESULTS OF 50 RUN OF THE PROPOSED MSDEP FOR CASE 1

Option#	Particle population	maximum iterations	Mutation probability (%)	%mp	Mean of C^{y}_{Prob} (k$)	SD of C^{y}_{Prob} (%)
1	**50**	**100**	**80**	**10**	**2,862**	**1.1**
2	40	125	80	10	**2,862**	1.9
3	20	250	80	10	2,899	2.0
4	10	500	80	10	3,020	2.4
5	60	83	80	10	2,896	**1.1**
6	50	100	80	30	2,879	2.2
7	50	100	80	50	**2,862**	1.7
8	50	100	80	70	2,901	1.7
9	50	100	80	90	2,873	2.2
10	50	100	90	10	2,874	1.8
11	50	100	70	10	2,908	1.9
12	50	100	50	10	2,882	1.8

B. *Case 2: realistic 747-bus distribution network*

In order to show the capability of the proposed MSDEP to handle a large-scale distribution network in reasonable time, a realistic 747-bus distribution network is studied, in this case. The specifications of this distribution network are provided in [26]. The average load growth for 5 years, in this case, is 1.5%. The maximum kVA of DR for residential, commercial, and industrial customers are 2, 10, and 200 kVA, respectively. The total probabilistic cost, in this case, is the lowest for the network expansion plan starting from Ref. Year 1. Therefore, the five-year planning results with Ref. Year 1 using the proposed risk-managed MSDEP is presented in TABLE IX. As seen, different POEx is selected in different years as the optimum level of demand that gives the minimum total cost of NSs and NNSs upgrades. The computational time for 5-year MSDEP for Case 2 based on the proposed approach in this paper is about 33 hours in MATLAB on Intel CORE i7-4770 PC with clock speed 3.4 GHz and 16 GB RAM.

TABLE IX

MSDEP RESULTS FOR 5-YEAR PLANNING WITH REF. YEAR 1

Ref. Year	**Upgrades**	**Planning Years**					**Total**
		1	2	3	4	5	
1	Trans.(kVA)	25	0	0	63	0	88
	Fix ESS (kVA)	5	340	890	2,645	1,345	5,225
	Cap.(kVAR)	490	210	500	1,480	975	3,655
	$DSNS^{y}$	POE90	POE80	POE70	POE50	POE40	-----
	C^{y}_{RMC}(k$)	183	166	369	609	940	2,268
	C^{y}_{Prob}(k$)	32,323	30,614	29,355	28,284	27,184	**147,760**

VII. Conclusion

A risk-managed least-cost planning approach for MSDEP is proposed to tackle load and renewable uncertainties though temporary generation and customer engagement in DR programs. The philosophy of the proposed approach is to determine the optimal level of demand at which the network should be upgraded using NSs while procuring temporary NNSs to treat the risk of exceeding demand above this level. The expected cost of procuring NNSs such as DR and temporary ESS/DG to manage the consequence of the risk due to uncertainties is defined as risk-managed cost. This proposed model determines the optimal combination of NSs and NNSs to meet the projected demand at the lowest cost while meeting technical constraints of the system and taking into account operation and maintenance, loss and reliability cost as well. To increase the computational efficiency of the MSDEP model for real-sized networks, an efficient heuristic-based solution approach coupled with a forward-backward decomposition algorithm is proposed. The risk-managed MSDEP tool is applied to IEEE 13-bus feeder and a realistic 747-bus distribution network to demonstrate the applicability and flexibility of proposed approach through different cases. The results show that it is cost-effective to upgrade the network using NSs for a lower level of demand while procuring NNSs to manage the risk of loads exceeding this level than investing in network capacities to overcome the uncertainties. Future works are including the reactive capability of PV interface in planning modeling and cross-connect design.

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