

A RISK-BASED FRAMEWORK TO OPTIMIZE DISTRIBUTED GENERATION INVESTMENT PLANS CONSIDERING INCENTIVE RELIABILITY REGULATIONS

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ABSTRACT

This paper develops a risk-based framework for maximization of distribution companies' profit, considering the implementation of incentive reliability regulations. In the proposed framework, various investment alternatives are considered. These alternatives are installation of distributed generation (DG) units as well as reinforcement of the existing feeders. Moreover, an efficient optimization framework based on genetic algorithm (GA) and dynamic programming technique are proposed to solve the introduced model. In order to demonstrate the application of the proposed framework, it is implemented on a test distribution network, and the obtained results are analyzed.

INTRODUCTION

The key role of electricity supply in modern societies has resulted in increasing demand for more reliable power systems. Since according to the statistics, a considerable share of customer interruptions (up to 90%) originates from faults and failures of electricity distribution networks [1], enhancing reliability level of distribution systems has gained special attention in recent years. In this respect, most of the national regulatory authorities around the world have implemented incentive-based mechanisms to motivate distribution companies (Discos) to enhance their service reliability [2], [3]. For instance, according to the Council of European Energy Regulators (CEER), incentive reliability regulations are implemented in 17 countries out of 26 investigated countries [4].

The main idea behind such incentive schemes is to provide financial rewards for companies whose reliability levels are higher than a specific benchmark and to penalize those with reliability levels less than a minimum limit [2], [5]. Hence, implementation of incentive reliability regulations establishes a direct link between Discos' revenue and their service reliability. This, in turn, makes a new challenge for Discos owing to the random nature of reliability indices [6]. In fact, implementation of such regulations puts a notable share of companies' profits at risk, due to the uncertain and random nature of reliability metrics. Therefore, it is crucial to capture these risks in the planning and operation studies of Discos. In this regard, in [6],

financial risk assessment under incentive reward-penalty schemes implementation is performed based on the historic reliability. In [7], a risk assessment method is proposed to quantify the uncertainty of reliability indices and their financial consequences in the incentive based reliability regulation regime. Employing sequential Monte Carlo simulation technique, authors in [8] obtained the probability distribution of reliability indices and quantified the financial risks imposed by incentive reliability regulations. Risk-based reconfiguration of distribution networks in the presence of reward-penalty regulation of reliability is investigated in [9]. A method for incorporating the risks of reward-penalty regulations into the optimal maintenance scheduling of distribution system assets is developed in [10]. Nonetheless, to the best of authors' knowledge, optimal planning of active distribution system considering the risks of incentive reliability regulations has not been addressed in the existing literature.

Accordingly, this paper aims at developing a risk-based framework to optimize the Discos' profit considering the implementation of incentive reliability regulations. In the proposed framework, various investment plans including installation of distributed generation (DG) units as well as reinforcement of feeders are considered. Moreover, an efficient optimization framework based on genetic algorithm (GA) and dynamic programming technique is utilized to solve the proposed model.

PROBLEM DESCRIPTION

As a consequence of regulatory reforms in electricity distribution sector, many regulatory authorities around the world have adopted various forms of incentive reliability regulations [11]. Such regulations generally aim at providing financial incentives to motivate distribution companies to provide satisfactory service reliability for customers. Among various incentive mechanisms adopted for regulating reliability, reward-penalty schemes are considered as the most effective tool for monitoring the widely-used system-oriented reliability indices, such as system average interruption duration index (SAIDI), and system average interruption frequency index (SAIFI) [2]. Although various forms of reward-penalty schemes have been designed and implemented in different countries, the

general form of reward-penalty scheme can be considered as Fig. 1 [3], [6], [7]. As depicted, reward-penalty scheme is a function that associates a reliability index to the financial rewards or penalties. According to this graph, a company receives bonus in case its reliability index is less than the reward point. Between reward point and reward cap point, the amount of this bonus increases with a rate known as incentive rate. In order to avoid excessive rewards, the value of bonus is limited to a maximum value named reward cap. Penalty zone has typically the same design, nonetheless, the reward-penalty graph can be asymmetric, i.e. having dissimilar shapes in reward and penalty zones [7].

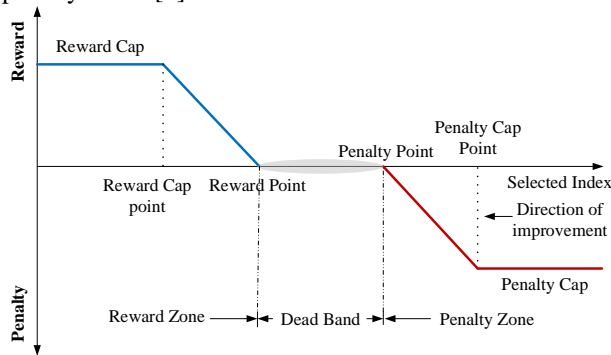


Fig. 1. Reward-penalty graph.

In order to calculate the financial value of rewards or penalties, regulators can simply put the ex-post reliability index of a given company into the reward-penalty function. In other words, since the regulators evaluate companies' performance in the end of a certain period, they have actual values of the reliability index. By contrast, companies, while performing planning studies, need to evaluate the network reliability and its financial consequences ex-ante. In fact, in order to improve service reliability and get the most out of incentive schemes, companies should carry out cost-worth analyses, in which an important task is quantifying the ex-ante reliability metrics. In this context, since reliability indices are principally random variables, studies can be conducted in two general approaches. One method is to attain the expected value of reliability indices using analytical techniques and subsequently calculate the financial outcomes accordingly. However, this technique is not quite accurate and also gives no information about the financial risks [7]. For instance, from the expected value perspective, all points on the dead band interval (see Fig. 1) are identical. Nonetheless, it is obvious that the risk rises as the expected value of the reliability index approaches the penalty point since slight random changes in reliability index can result in penalties [6], [7].

Another technique is to perform risk-based analysis, which requires probability distribution function (PDF) of the reliability indices. Since attaining such PDFs using analytical methods is too complex to be applicable for real networks, Monte Carlo simulation is employed for extracting the PDF of reliability indices [8], [12].

On these bases, in the following, a risk-based method is

developed for optimal reliability-based distribution system planning. In the proposed model, installation of DG units as well as reinforcement of the feeders are considered as the alternate plans for reliability enhancement and network expansion. In other words, DG installation is considered as the main solution for improving the reliability of distribution grid. Moreover, for accurate modeling of DGs' impact on investment cost savings and loss reduction, optimal reinforcement of distribution feeders is also addressed.

PROBLEM FORMULATION

As expressed in (1), objective function of the proposed risk-based optimal DG investment problem is the weighted sum of expected value of total cost, CF , and a risk measure, RM . The weighting factor, $0 \leq \beta \leq 1$, which is set by the distribution system planner, models the tradeoff between CF and RM . Risk-averse planners typically choose higher values of β to highlight the importance of risk measure in the objective function, while risk-neutral decision makers would set it to a value close to zero [13].

$$\min OF = (1 - \beta)CF + \beta RM \quad (1)$$

$$CF = CDG + CFR + CLoss + CR \quad (2)$$

$$CDG = \sum_{t=1}^T \sum_{i=1}^{N_c} \sum_{k=1}^{N_a} \left(\delta_{t,k} n_{t,i,k} IC_{i,k}^{DG} + \sum_{ll=1}^{N_{ll}} \frac{P_{t,i,k,ll}^{DG} D_{ll} NOC_{t,k,ll}^{DG}}{(1+r)^{t-1}} \right) \quad (3)$$

$$\delta_{t,k} = \frac{1 - (1+r)^{-(T-t+1)}}{(1+r)^{t-1} (1 - (1+r)^{-UL_k})} \quad (4)$$

$$NOC_{t,k,ll}^{DG} = FC_{t,k,ll} + MC_{t,k} - EP_{t,ll} - RHI_{t,k,ll} \quad (5)$$

Expected cost CF is further expressed in (2), which is comprised of DG costs (CDG), feeder reinforcement cost (CFR), cost of network energy losses ($CLoss$), as well as reliability related costs (CR). According to (3), CDG is present value of investment and operating costs of DG units, where $\delta_{t,k}$ is present value factor for investment costs which is obtained from (4). Moreover, $n_{t,i,k}$ is an integer variable denoting the number of DG units of type k installed at candidate node i in time stage t , $IC_{i,k}^{DG}$, $NOC_{t,k,ll}^{DG}$ are investment and net operating costs of DGs, $P_{t,i,k,ll}^{DG}$ is the power produced by each DG unit, and D_{ll} is total duration of load level ll . Moreover, T , N_c , N_a , and r are planning horizon, number of candidate nodes for installation of DGs, number of candidate alternatives for DG units, and interest rate, respectively. $NOC_{t,k,ll}^{DG}$ is, in other words, net production cost of DG units and as can be inferred from (5), it is formulated in terms of fuel cost ($FC_{t,k,ll}$), maintenance cost ($MC_{t,k}$), electricity price ($EP_{t,ll}$), and finally the incomes from recovered heat ($RHI_{t,k,ll}$), in case the associated DG is operated as a combined heat and power (CHP) unit.

Operation of DG units are also subject to logical and technical constraints (6), (7), where Ca_k^{DG} is the capacity of DG unit of type k , and $Tca_t^{DG,Max}$ is the maximum permissible total DG capacity in the network. Accordingly, equation (6) sets the maximum power production of DG units to the installed capacity, and constraint (7) limits the maximum penetration level of DG units within the network.

$$0 \leq P_{t,i,k,\ell}^{DG} \leq \sum_{\tau=1}^t n_{\tau,i,k} Ca_k^{DG} \quad (6)$$

$$\sum_{\tau=1}^t \sum_{i=1}^{N_i} \sum_{k=1}^{N_k} n_{\tau,i,k} Ca_k^{DG} \leq TCa_t^{DG,Max}, \quad \forall t \in \{1, \dots, T\} \quad (7)$$

Present value of the feeders reinforcement cost is calculated using (8) in which $x_{t,f,k}$ is a binary investment variable that becomes one if investment alternative k is performed on feeder f at time stage t . Furthermore, $RC_{f,k}$ and $SR_{t,f}$ are reinforcement cost and salvage revenue, respectively.

$$CFR = \sum_{t=1}^T \sum_{f=1}^{N_f} \sum_{k=1}^{N_k} \frac{1}{(1+r)^{t-1}} x_{t,f,k} (RC_{f,k} - SR_{t,f}) \quad (8)$$

Present value of the total energy loss cost during the planning horizon is also formulated in (9), where $R_{t,f}$ is resistance of feeder section f and $I_{t,f,\ell}$ is the current magnitude. It is worth mentioning that the line resistance can change depending on the feeder reinforcement decisions, hence, subscript t is used for $R_{t,f}$.

$$C_{Loss} = \sum_{t=1}^T \sum_{f=1}^{N_f} \sum_{\ell=1}^{N_\ell} \frac{1}{(1+r)^{t-1}} R_{t,f} I_{t,f,\ell}^2 D_{\ell} \quad (9)$$

As formulated in (10), reliability related costs, CR , is comprised of expected value of financial consequences of reward-penalty schemes ($CPRS_t$), and expected revenue lost due to network interruptions (CU_t), which are further expressed as (11), and (12), respectively. In these equations, PRS_t and ENS_t are random variables associated with reward-penalty cost and annual energy not served of the network, respectively, and ER_t is the amount of revenue earned by distribution company for delivering electricity to the customers (\$/kwh).

$$CR = \sum_{t=1}^T \frac{1}{(1+r)^{t-1}} (CPRS_t + CU_t) \quad (10)$$

$$CPRS_t = E[PRS_t] \quad (11)$$

$$CU_t = ER_t E[ENS_t] \quad (12)$$

Finally, the risk measure is attained using (13) as the present value of conditional value at risk with $\alpha\%$ level

($CVaR_\alpha$) of reliability oriented costs including the cost imposed by reward-penalty schemes as well as revenue lost due to power interruptions. In other words, $CVaR_\alpha(PRS_t + ER_t ENS_t)$ is the expected value of the worst (highest) α percent of the reliability related costs, i.e. $PRS_t + ER_t ENS_t$ values. PRS_t is also calculated from the reward-penalty curve depicted in Fig. 1. In this context, by putting the values of the random variable, RI_{ri} , associated with each reliability index ri in the corresponding reward-penalty function, F_{ri}^{RPS} , PRS_t can be obtained from (14).

$$RM = \sum_{t=1}^T \frac{1}{(1+r)^{t-1}} CVaR_\alpha(PRS_t + ER_t ENS_t) \quad (13)$$

$$PRS_t = - \sum_{ri=1}^{N_{ri}} F_{ri}^{RPS}(RI_{ri}) \quad (14)$$

It is worth noting that positive values of PRS_t correspond to the penalty and negative values indicate reward. In (14), N_{ri} is the number of reliability indices for which reward-penalty scheme are implemented and RI_{ri} is the random variable associated with reliability index ri . For instance, in Italy, two reward-penalty schemes based on SAIFI and SAIDI have been implemented [4], hence, $N_{ri}=2$ and two random variables should be considered for these indices.

OPTIMIZATION METHOD

General structure of the proposed technique for solving the model presented in the previous section is depicted in Fig. 2. According to this flowchart, at each iteration of genetic algorithm (GA), installation time, type and location of DGs are determined through setting integer variables $n_{i,k}$ (see equation (3)) subject to constraint (7). Subsequently, time-sequential Monte Carlo Simulation (MCS) method is used to obtain the probability distribution function (PDF) of the resulted reliability indices (i.e. SAIDI and EENS) based on the method proposed in [12] with a slight modification for improving the convergence characteristic and simulation time. The associated expected value as well as risk measure of the reliability related costs for the DG

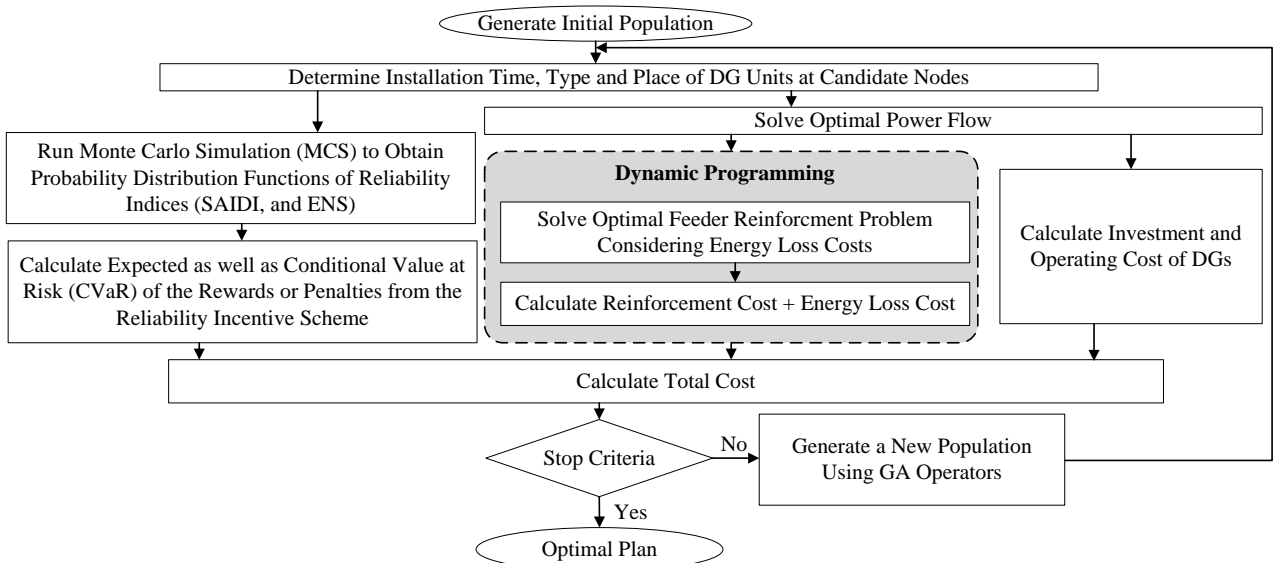


Fig. 2. Structure of the proposed optimization framework.

deployment plan are then calculated from (10) and (13), respectively.

On the other hand, optimal power flow (OPF) problem is solved for different load levels ll during the planning horizon and power generation of DGs ($P_{t,i,k,ll}^{DG}$) as well as feeder currents ($I_{i,f,ll}$) are determined. Subsequently, the associated investment and operating costs of DG units are calculated using (3). Moreover, the novel dynamic programming-based method introduced in [14] is employed for optimizing the distribution feeder reinforcement plans considering the obtained feeder flows from the OPF. In this respect, total costs of grid reinforcement and energy losses are calculated by (8) and (9), respectively. The aggregated cost and risk is then calculated for different GA candidate solutions. As shown in Fig. 2, this process continues until the stopping criteria for GA algorithm are met. In this context, either the change of objective function should be lower than a predetermined threshold, or maximum number of iterations are reached. In the following section, this framework is applied to a test system to obtain the optimal DG investment plan.

NUMERICAL STUDY

In order to demonstrate the application of the proposed framework, it is implemented on test distribution network connected to bus 2 of the Roy Billinton Test System (RBTS) [15]. This test system has 36 overhead line sections, 20 distribution transformers, and 22 load nodes. In the studies, a five-year planning horizon is considered and a 4 percent interest rate is assumed. Nodal demands are modeled through a four-level load duration curve with 100, 80, 60, and 40 percent of the nodal peak demand and duration of 1095, 2190, 3650, and 1825 hours per year, respectively. Electricity price at these load levels are assumed equal to 120, 70, 60, and 45 dollars per MWh, respectively. Moreover, annual load growth rate is set to 5 percent.

With respect to the investment alternatives, seven options are considered for feeder reinforcement, and three different technologies are taken into account for DG units. Furthermore, three load points are selected as candidate nodes for DG installation.

A reward-penalty scheme based on the SAIDI index is assumed as the incentive reliability regulation applied to the investigated distribution company. Reward point, penalty point, reward cap point and penalty cap point of this scheme are set to 15, 18, 3, 30 hours per year, respectively. Reward and penalties are also capped at 600 and 900 k\$, respectively. Additionally, in order to perform Monte Carlo simulation, a period of 100,000 years is considered, and exponential distribution function is used for obtaining the random time to failure values and repair times of network elements.

Present values of different cost terms as well as the reliability indices for Base Case and four other cases (corresponding to different β values) are reported in Table 1. In this table, the reliability indices represent the five-

year average of the expected values.

Table 1. Numerical study results (All costs are in M\$)

	Base Case	$\beta=0$	$\beta=0.3$	$\beta=0.9$	$\beta=1$
CF	8.158	4.478	4.727	5.413	7.232
RF	2.275	0.902	0.683	0.560	0.475
CFR+CLoss	9.678	5.979	6.191	6.918	7.467
CR	-1.520	-1.809	-1.851	-1.918	-1.922
CDG	0	0.308	0.387	0.413	1.687
SAIDI (h/year)	8.30	6.95	6.77	6.47	6.45
ENS (MWh)	144.87	117.67	114.08	111.20	108.88

In the Base Case, no DG units are installed in the system, and only feeder reinforcements are considered for addressing the annual load growth. As can be observed, although the expected value of Disco's reliability falls in the reward zone and CR is negative (similar to the other cases), the associated risk is higher than the other cases.

On the other hand, as depicted in Fig. 3, there is a trade-off between the expected value of cost (CF) and risk measure (RM). In this context, in order to restrict the risks, the expected value of investment costs has to be increased. In addition, it is interesting to note that reinforcement costs would increase as the value of β increases. In this regard, it can be seen that installation of DG units would generally reduce the feeder investment costs (compare the third row for Base Case and the other cases). However, risk reduction would increase the line investment costs. This is because with small values of β , Disco will try to optimize the DG installation plans such that line investments as well as expected reliability costs are minimized. In contrast, with higher β values, the Disco would prefer to install the DGs at locations where maximum improvement on reliability is attained, at the expense of total costs increment.

Probability distribution of SAIDI for the two extreme cases of β are illustrated in Figs. 4 and 5. Comparing these charts, it can be seen that for $\beta=1$, probability of having lower SAIDI values is higher; in other words, the chance of gaining reward would be higher, according to Fig. 1. Additionally, Probability distribution of ENS for these cases as well as the associated fitted lognormal curves, are compared in Fig. 6. Similar to the previous observation, ENS index also improves at $\beta=1$, since lower ENS values have higher probabilities.

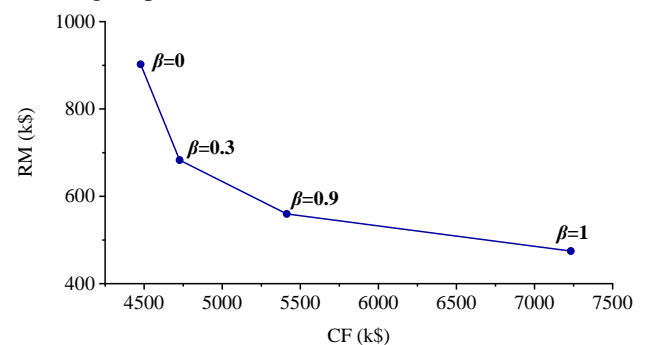
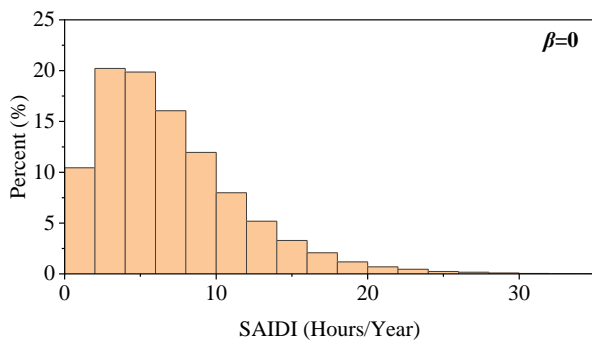
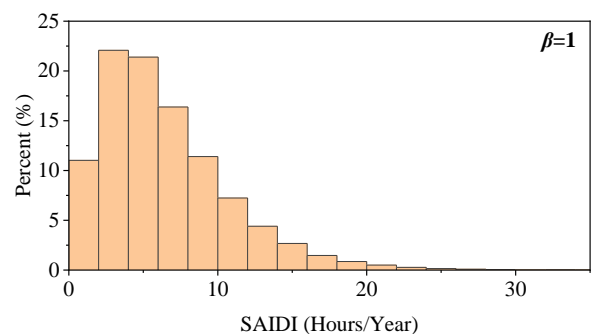
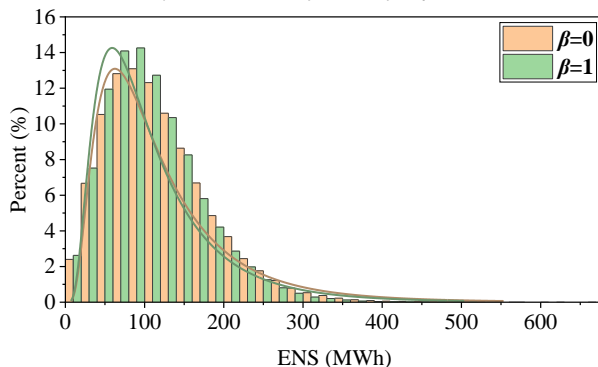


Fig. 3. Risk measure (RM) versus expected total cost (CF) for various weighting factors (β).


 Fig. 4. Probability distribution of SAIDI for $\beta=0$.

 Fig. 5. Probability distribution of SAIDI for $\beta=1$.

 Fig. 6. Probability distribution of ENS for $\beta=0$ and $\beta=1$.

CONCLUSION

In this paper, a risk-based framework for Discos profit maximization in view of incentive reliability regulations is presented. In this framework, various investment alternatives for DG installation and feeder reinforcement are investigated. Moreover, an efficient optimization framework based on GA and dynamic programming are utilized to solve the proposed model. The presented framework is implemented on a test system, and the obtained results demonstrate its effectiveness.

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