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Research Paper

A Cost-Effective Trade-off in Distribution System Expansion Planning Between Construction of Conventional/Renewable Distributed Energy Sources in Long Term

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Abstract— *Nowadays, with the detrimental impacts of air pollution on human health and its significant societal expenses, it has been imperative to utilize renewable energy sources (RESs) and energy storage systems (ESSs). This study introduces a new objective function aimed at achieving a long-term optimal plan where it contrasts the outcomes of meeting network load demand with and without the integration of renewable/non-renewable distributed energy resources (DERs). The analysis considers installation and operational costs, addressing uncertainties through Monte-Carlo and scenario-based methodologies. The proposed problem is structured as a convex optimization model. Simulations are conducted on the IEEE 33-bus system, showcasing the model's efficacy through cost efficiency and reduced emission expenses. The study confirms that the investment in renewable energy resources and ESS units can be recouped in less than five years. It was observed that in the long-term, there is a cost reduction of 29.4% when DER units are incorporated. Also, the emission cost for the horizon year is diminished by 43.2% compared to the case where the DERs are absent.*

Keywords—Distribution system planning, renewable energy sources, energy storage systems, uncertainty, convex optimization.

NOMENCLATURE

Indices

i, j	Buses
S	Uncertainty scenario
T	Time (hr)
Y	Planning horizon year

Parameters

$\Pr ob_s$	Probability of each uncertainty scenario
D	Duration of days in year
DGE	CO_2 emission due to power generation of DGs (tons/MWhr)
DG^{Max}	Maximum number of DG units that can be allocated in the whole network
EFC/EFD	Charge/discharge efficiency of ESS units
emc	Emission cost ($/ton)
ESS^{Max}	Maximum number of ESS units that can be allocated in the whole network
GE	CO_2 emission due to power received from the upward network (tons/MWhr)
$I_{i,j}^{Max}$	Maximum lines ampacity in ampere
$Infr$	Inflation rate (%)
$Intr$	Interest rate (%)
IN^{DG}	Gas turbine's (synchronous DG's) installation cost ($/MVA)
IN^{ESS}	Installation cost of ESS units ($/MWhr)
IN^{WT}	Wind turbine's (WT's) installation cost ($/MVA)
P_i^L/Q_i^L	Peak value of active/reactive load demand
$P_{i,t,s}^{WT,cap}$	Capacity of wind turbine
P_{Max}^G/Q_{Max}^G	Maximum active/reactive power injected from upstream network
P_{Max}^{ESS}	Maximum active power of ESS units
PF	Generation power factor of synchronous DG units
PW_y	Present worth factor
$R_{i,j}^{Line}$	Line resistance
S_{Max}^{DG}	Capacity of synchronous generators
SOC^{Max}	Maximum energy storage capacity of ESS units
$V_{t,s}^{wind}$	Wind speed
WT^{Max}	Maximum number of WT units that can be allocated in the whole network
$X_{i,j}^{Line}$	Line reactance
$\lambda_{t,s}$	Load level factor
$\Pr^{DG}$	Operation cost for synchronous DG ($/MWhr)
$\Pr^{SUB}$	Price of energy purchased from upward grid ($/MWhr)
P_{rated}	Rated power of wind turbines
V_{Max}/V_{Min}	Maximum/minimum voltage magnitude for buses
V_{rated}	Rated speed of wind turbine
$V_{c_{in}}/V_{c_{out}}$	Cut-in/cut-out speeds of wind turbine

Sets

Ω_N	Set of buses
Ω_S	Set of uncertainty scenarios
Ω_T	Set of time

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Ω_Y Set of studied years
Ω_{Slack} Set of slack bus

Variables

DG_i Binary variable for allocation of new dispatchable DG units
EMC_y Total emission cost of CO_2 per year
ESS_i Binary variable to allocate new ESS units
$ich_{i,t,s}/idch_{i,t,s}$ Charge/discharge binary variable of ESS
IC^{DG} Total Installation cost for synchronous DGs
IC^{ESS} Total installation cost of ESS units
IC^{WT} Total installation cost of wind turbine units
OC_y^{DG} Total operation cost of dispatchable DGs and wind turbines per year
OC_y^{SUB} Total cost of purchasing energy from upstream network per year
OF_y Main objective function
$P_{i,j,t,s}^{net}/Q_{i,j,t,s}^{net}$ Active and reactive powers flowing in the feeders
$P_{i,t,s}^{G}/Q_{i,t,s}^{G}$ Active/reactive power received from the transmission system
$P_{i,t,s}^{DG}/Q_{i,t,s}^{DG}$ Active/reactive power generated by synchronous DGs
$P_{i,t,s}^{WT}$ Active power generated by WTs
$PD_{i,t,s}/PC_{i,t,s}$ Charge/discharge of ESS units
$S_{i,t,s}^{G}$ Apparent power injected to the network from the upstream network
$SOC_{i,t,s}$ State of charge for ESS units
WT_i Binary variable for allocation of new wind turbines
$J_{i,j,t,s}$ Square of lines' current magnitude
$U_{i,t,s}$ Square of bus voltage
$V_{i,t,s}$ Voltage of buses

1. INTRODUCTION

Given the evident increase in load demand over recent years, a fundamental inquiry emerges within the context of long-term economic distribution system planning. This inquiry pertains to the comparative economic viability between two options: expansion of upstream network encompassing power generation and transmission infrastructure, or the deployment of distributed energy resources (DER) units near the loads [1, 2]? To address this question, a comprehensive assessment and comparison of four key factors is imperative:

- Installation and expansion cost of new substations/DERs
- Expansion cost of transmission lines
- Power loss cost
- Air pollution cost

Due to the destructive effects of CO_2 gas in air pollution and the significant costs imposed on society as a result of it, the management of CO_2 emission has become one of the most crucial issues in the world [3]. Also, reducing power losses in the network has always been one of the main concerns of distribution network operators (DNOs) [4]. Therefore, the DNOs should have a special view on minimizing CO_2 emission as well as power loss reduction in today's power systems. One of the alternatives to achieve these goals is the use of RESs and ESS units in modern distribution networks. The use of DERs and ESSs in distribution network brings many benefits such as deferring reinforcements, reducing the installation and operational costs, relieving lines and substations' capacity, peak shaving, reducing the power loss and voltage drop, and increasing the network reliability and resiliency [5–7].

As mentioned, the presence of DERs in the network is highly beneficial. This matter will be more highlighted regarding the load demand increase in the coming years. Due to the load increase in the long term, the network costs (including expansion and operation costs) would be much higher without the presence of DERs. Furthermore, due to the load demand increase, especially at peak load hours, the power loss and emission costs will be increased accordingly. In this regard, several researches have addressed the planning issue of distribution systems to satisfy the load growth considering different technical and operational constraints, which are reviewed subsequently.

In [8], the effect of energy storage systems and renewable energy sources on the optimization of network security index, network reliability index, and system operating and investment costs has been investigated. In addition, the switches status, ESSs charging/discharging pattern, and the active power values of diesel generators are optimally determined. The model of this work is not convex, and hence, finding of global optimum solution is not guaranteed. Ref. [9] proposes a novel comprehensive optimization model for the expansion planning of a resilient network. In this paper, optimal placement and capacity of substations and DG units as well as optimal feeders routing and hardening are obtained. In addition, to achieve a resilient network, the presented model has been tested in different scenarios. In [10], in order to improve power generation quality and reduce the effect of renewable energy sources fluctuations, optimal sizing and siting of ESS units have been determined by considering costs minimization. The simulation results were obtained by two methods of genetic algorithm (GA) and particle swarm optimization (PSO) on the IEEE 33-bus system. In this paper, the installation cost of ESS and DER units have not been considered. Also, the optimization model is non-linear and non-convex. A new energy management system is presented in [11] to form a micro-grid with various renewable energy resources and energy storage systems. Also, a new mathematical model is used for the PV units operating in the micro-grid. A modified bat algorithm (MBA) is employed to achieve an optimal energy management of micro-grid under uncertainty condition. The simulation results indicate that the MBA is faster and more accurate than the GA and PSO algorithms. Also, it is demonstrated that the use of renewable energy sources has a great effect on the system power loss reduction. The employed optimization methods are of meta-heuristic types obtaining local optimum solutions. In [12], a convex formulation is presented to minimize the power loss in normal operating mode as well as load shedding in emergency condition after occurrence of natural disasters. A Line flow based algorithm is used for AC power flow of distribution system. Also, the impact of conventional and renewable energy sources and ESS units on the power flow is investigated. The simulations have been implemented in GAMS through a mixed-integer quadratically-constrained programming (MIQCP) model where the GUROBI solver has been employed for the optimization purpose. This papers' result could be improved by allocating DG units as well as ESS units. Because of annual load demand increase, there will be lines and transformers congestion as well as buses voltage drop. In this regard, in [13], the use of renewable DGs as an impressive way to deal with these problems is suggested. A hybrid method based on moth-flame optimization (MFO) algorithm is employed to determine the optimal location of DG units. The proposed method is applied on the IEEE 69-bus system, where the results show power loss reduction and improvement of buses voltages. This paper has not regarded uncertainty of loads and DG units. In addition, the cost, as an important issue, has not been under consideration. In order to reduce the effects of power fluctuations in renewable DGs and their uncertainty, a new technique is presented in [14] to optimally determine the location and size of each source in distribution systems with a radial structure. Uncertainty scenarios are generated by implementing Monte-Carlo simulation, where the backward reduction algorithm is employed to reduce the number of scenarios for lowering the computational complexity. In addition, a multi-objective function is considered to minimize expected total cost, the expected total voltage deviation, and the expected total emissions. The proposed method is applied on the IEEE 33-bus system and also on an actual distribution network in Portugal. A convex optimization approach is given in [15] having two objective functions the first of which includes energy loss minimization under normal operation condition, and the second one is the load curtailment reduction under emergency conditions.

For this aim, conventional and renewable DGs as well as ESS units are optimally allocated, and also, the micro-grids (MGs) are optimally configured. Efficiency of the presented method from the viewpoints of energy loss minimization and resiliency improvement is investigated through different experiment in GAMS. The model has not been evaluated from the cost point of view.

Reviewing the literature shows that each of the works has not considered one or more of the following issues:

- Consideration of renewable and non-renewable DGs in long-term expansion planning of distribution systems;
- Using convex formulations such that that the optimality of the solution is guaranteed;
- Considering environmental emission in the planning;
- Uncertainty consideration

In the current paper, total cost (expansion cost and operation cost) caused by impact of power loss and air pollution is compared to the effect of construction (or not) of new renewable/non-renewable DGs and ESSs in long term. In fact, the main aim of this paper is to compare two states: if the investment on the network expansion and new DERs installation is economical in long-term from the viewpoint of power loss and emission costs reduction? Or there is no need to this issue, and the power loss and emission costs do not have high effect, and they can be neglected? The planning options are composed of allocation of dispatchable and renewable energy based DGs as well as ESSs. All the results have been calculated by taking into account the uncertainty of the load and wind speed obtained by the Monte Carlo method. The investment, operational, and emission costs are introduced into the objective function, and all of problem limitations are considered. Also, the LFB (line-flow-based) AC power flow relations are utilized. All the relations are convexfied such that a MIQCP optimization model is composed. The proposed model is accomplished in GAMS where the global optimum solvers are employed to obtain the solutions.

The main contribution of this paper can be outlined as follows:

- Presenting a convex optimization model for distribution network expansion planning in the long-term
- Investment and operation costs have been considered as well as emission costs
- Utilizing a Monte-Carlo scenario-based method for uncertainty consideration
- A new cost-effective insight to compare renewable/non-renewable DG units expansion

2. Problem formulation

2.1. Uncertainty modeling

In this paper, load demand and wind speed, as two sources of uncertainty have been considered. The wind speed uncertainty is modeled by the Weibull distribution. The probability density function (PDF) of the wind speed is according to Eq. (1) [16], where V is the wind speed, and K and C are constant parameters representing shape and scale parameters, respectively. These parameters are dependent on geographic location of the wind turbine, and they usually have hourly/daily/seasonal changes.

$$f\left(v\right)=\frac{k}{c}\left(\frac{V}{c}\right)e^{-\left(\frac{V}{c}\right)^{\alpha}} \tag{1}$$

For the load demand, the normal distribution is utilized to model its uncertain behavior [16]. The PDF of load demand is as Eq. (2), where μ_P and σ_P are mean and standard deviation, respectively. These parameters are taken from the historical data for each hour of the day in the current problem.

$$f\left(P\right)=\frac{1}{\sqrt{2\pi}\sigma_P}e^{-\frac{(P-\mu_P)^2}{2\sigma_P^2}} \tag{2}$$

In this paper, the PDFs of Eqs. (1) and (2) are employed to generate wind speed and load demand scenarios using the Monte-Carlo simulation. By the aid of the MCS, a large number of uncertainty scenarios are generated. Then, the k-means clustering algorithm is utilized to cluster the scenarios and reduce the number of them to a reasonable extent in order to lower the computational burden. The details of MCS and k-means techniques have been given in [17] and [18].

2.2. Objective function

The main objective function is according to Eq. (3), which includes investment cost of new DERs and ESSs, operation costs, and emission cost of CO_2 for the horizon year of 20. In Eq. (4), the objective function is calculated for each case study. Eqs. (5)-(7) show investment cost of DG, WT, and ESS units, respectively. Also, operation cost for the energy injected to the system from the upstream network and DG units are given in Eqs. (8) and (9), respectively. Eq. (10) denotes the emission cost corresponding to CO_2 emission due to power generation in upward grid and DG units, respectively. As seen in the equations, the present worth values of operational costs are employed by using PW_y factor which is dependent on interest and inflation rates. For convenience, definition of parameters and variables is given in the nomenclature.

$$\forall i,j\in\Omega_N,\forall t\in\Omega_T,\forall s\in\Omega_S,\forall y\in\Omega_Y:$$

$$\text{Main Objective Function}=\text{Min}(OF_y)\quad;\forall y=20 \tag{3}$$

$$\begin{aligned}OF_y=IC^{DG}+IC^{WT}+IC^{ESS}+\\ OC_y^{SUB}+OC_y^{DG}+EMC_y\end{aligned} \tag{4}$$

$$IC^{DG}=\sum_{i\in\Omega_N}DG_iIN^{DG} \tag{5}$$

$$IC^{WT}=\sum_{i\in\Omega_N}WT_iIN^{WT} \tag{6}$$

$$IC^{ESS}=\sum_{i\in\Omega_N}ESS_iIN^{ESS} \tag{7}$$

$$\text{OC}_y^{SUB}=D\times PW_y\sum_{i\in\Omega_N}\sum_{t\in\Omega_T}\sum_{s\in\Omega_S}S_{i,t,s}^{G}\Pr ob_s\lambda_{t,s}\text{Pr}^{SUB} \tag{8}$$

$$\text{OC}_y^{DG}=D\times PW_y\sum_{i\in\Omega_N}\sum_{t\in\Omega_T}\sum_{s\in\Omega_S}P_{i,t,s}^{DG}\Pr ob_s\text{Pr}^{DG} \tag{9}$$

$$\begin{aligned}&EMC_y=D\times PW_y\times\\&emc\sum_{i\in\Omega_N}\sum_{t\in\Omega_T}\sum_{s\in\Omega_S}P_{i,t,s}^{G}GE\Pr ob_s+P_{i,t,s}^{DG}DGE\Pr ob_s\end{aligned} \tag{10}$$

$$PW_y=\sum_{y\in\Omega_Y}\left(\frac{1+Infr}{1+Intr}\right)^y \tag{11}$$

2.3. Problem constraints

Different constraints govern the proposed model, which are detailed in the following.

A) Power flow constraints

The nature of basic AC power flow equations is non-linear and non-convex. With the aim of convexifying complex calculations and reduce the problem solving time, the line flow based (LFB) model is used [9]. Regarding binary variables of DERs installation, the obtained convex model is mixed-integer quadratically-constrained programming (MIQCP) which the global optimum solvers such as GUROBI and CPLEX can handle and solve it in GAMS [19].

$$\begin{aligned}&\sum_{j\in\Omega_N} A_{\ell i}P^{net}_{i,j,t,s} = P^{G}_{i,t,s} + P^{DG}_{i,t,s} + P^{WT}_{i,t,s} + PD_{i,t,s} - \\ &PC_{i,t,s} - \lambda_{t,s}P^{L}_{i} - \sum_{j\in\Omega_N} B_{\ell i}R^{Line}_{i,j}J_{i,j,t,s}\end{aligned} \tag{12}$$

$$\begin{aligned}&\sum_{j\in\Omega_N} \mathrm{A}_{\ell i}\mathrm{Q}^{\mathrm{net}}_{i,j,t,s} = Q^{G}_{i,t,s} + Q^{DG}_{i,t,s} - \lambda_{t,s}Q^{L}_{i} - \\ &\sum_{j\in\Omega_N} B_{\ell i}X^{Line}_{i,j}J_{i,j,t,s}\end{aligned} \tag{13}$$

$$\begin{aligned}&U_{i,t,s} - U_{j,t,s} = +2\left(R^{Line}_{i,j}P^{net}_{i,j,t,s} + X^{Line}_{i,j}Q^{net}_{i,j,t,s}\right) + \\ &\left[\left(R^{Line}_{i,j}\right)^2 + \left(X^{Line}_{i,j}\right)^2\right]J_{i,j,t,s}\end{aligned} \tag{14}$$

$$\left(P^{net}_{i,j,t,s}\right)^2 + \left(Q^{net}_{i,j,t,s}\right)^2 \le J_{i,j,t,s}U_{j,t,s} \tag{15}$$

$$P^{net}_{i,j,t,s} = -P^{net}_{j,i,t,s} \tag{16}$$

$$Q^{net}_{i,j,t,s} = -Q^{net}_{j,i,t,s} \tag{17}$$

$$\left(P^{G}_{i,t,s}\right)^2 + \left(Q^{G}_{i,t,s}\right)^2 \le \left(S^{G}_{i,t,s}\right)^2 \tag{18}$$

Eqs. (12) and (13) represent balance of active and reactive powers at bus i, in different time periods, and scenarios. $A_{\ell i}$ is the $\ell i - th$ element of the bus-line matrix. This element will be 1/-1 if bus i is the sending/receiving bus of line in path $i-j$. Otherwise, it is 0. $B_{\ell i}$ is similar to $A_{\ell i}$ if the "1" elements are replaced by 0. Eq. (14) denotes the relation between voltages of two nearby buses. Eq. (15) gives the relation among power, voltage and current. Active and reactive powers of sending and receiving buses are expressed in Eqs. (16) and (17). It is worth mentioning that $P^{net}_{j,i,t,s}$ and $Q^{net}_{j,i,t,s}$ are active and reactive powers transferred from node j to node i at the side of node i, i.e., the power loss of line $i-j$ has not been regarded in Eqs. (16) and (17). Eq. (18) illustrates nodal relations between active, reactive, and apparent powers. In Eqs. (19)-(21), buses' voltages and branches' currents constraints have been given. Limitations of injected power from the upstream network are given in Eqs. (22) and (23).

$$\begin{cases} V_{i,t,s} = 1 & ;\forall i \in \Omega_{Slack} \\ V_{Min} \le V_{i,t,s} \le V_{Max} & ;otherwise \end{cases} \tag{19}$$

$$U_{i,t,s} = \left(V_{i,t,s}\right)^2 \tag{20}$$

$$0 \le J_{i,j,t,s} \le \left(I^{Max}_{i,j}\right)^2 \tag{21}$$

$$\begin{cases} 0 \le P^{G}_{i,t,s} \le P^{G}_{Max} & ;\forall \mathrm{i} \in \Omega_{Slack} \\ P^{G}_{i,t,s} = 0 & ;otherwise \end{cases} \tag{22}$$

$$\begin{cases} 0 \le Q^{G}_{i,t,s} \le Q^{G}_{Max} & ;\forall \mathrm{i} \in \Omega_{Slack} \\ Q^{G}_{i,t,s} = 0 & ;otherwise \end{cases} \tag{23}$$

B) Constraints of synchronous DGs

Eqs. (24)-(26) represent active/reactive power generation limits of synchronous DG units. In order to allocate the DG units, a binary variable which is named DG_i has been used, and the number of installed DG units throughout the network must be lower than DG^{Max}.

$$\text{-}\tan\left(\cos^{-1}(PF)\right)P^{DG}_{i,t,s} \le Q^{DG}_{i,t,s} \le \tan\left(\cos^{-1}(PF)\right)P^{DG}_{i,t,s} \tag{24}$$

$$\left(P^{DG}_{i,t,s}\right)^2 + \left(Q^{DG}_{i,t,s}\right)^2 \le DG_i\left(S^{DG}_{Max}\right)^2 \tag{25}$$

$$\sum_{i\in\Omega_N} DG_i \le DG^{Max} \tag{26}$$

C) Constraints of ESS units

ESS units will have significant role in efficient operation of distribution network if they are optimally located and scheduled. Eq. (27) denotes state of charge (SOC) of ESS unit installed at bus i, at time period t, in each uncertainty scenario. In Eq. (28), ESS_i is a binary variable indicating installation status of ESS unit at bus i. Eqs. (29) and (30) express charge/discharge power of each ESS unit. Based on Eq. (31), charging/discharging of storage devices cannot be occurred at the same time. Also, Eqs. (32) and (33) guarantee that the number of energy storage units must be lower than maximum permissible number, and the SOC at the final hour must be equal to initial charge, respectively.

$$\mathrm{SOC}_{i,t,s} = SOC_{i,(t-1),s} + \left(PC_{i,t,s}EFC\right) - \left(\frac{PD_{i,t,s}}{EFD}\right) \tag{27}$$

$$0 \le SOC_{i,t,s} \le ESS_iSOC^{Max} \tag{28}$$

$$0 \le PC_{i,t,s} \le ich_{i,t,s}P^{ESS}_{Max} \tag{29}$$

$$0 \le PD_{i,t,s} \le idch_{i,t,s}P^{ESS}_{Max} \tag{30}$$

$$ich_{i,t,s} + idch_{i,t,s} \le ESS_i \tag{31}$$

$$\sum_{i\in\Omega_N} ESS_i \le ESS^{Max} \tag{32}$$

$$SOC_{i,t_{24},s} = SOC_{i,t_0,s} = ESS_iSOC_0 \tag{33}$$

D) Constraints of WT units

Eqs. (34)-(36) are established for WT units' installation and operation limits, based on which the generated active power of wind turbine is dependent of the wind speed and characteristics of the WT [15]. The parameters of the relations have been defined in the nomenclature.

$$\mathrm{P}^{WT,cap}_{i,t,s} = \begin{cases} 0 & ;\forall V^{wind}_{t,s} < V_{c_{in}} \\ P_{rated}\left(\frac{V^{wind}_{t,s} - V_{c_{in}}}{V_{rated} - V_{c_{in}}}\right) & ;\forall V_{c_{in}} \le V^{wind}_{t,s} < V_{rated} \\ P_{rated} & ;\forall V_{rated} \le V^{wind}_{t,s} < V_{c_{out}} \\ 0 & ;\forall V^{wind}_{t,s} \ge V_{c_{out}} \end{cases} \tag{34}$$

$$0 \le P^{WT}_{i,t,s} \le WT_iP^{WT,cap}_{i,t,s} \tag{35}$$

$$\sum_{i\in\Omega_N} WT_i \le WT^{Max} \tag{36}$$

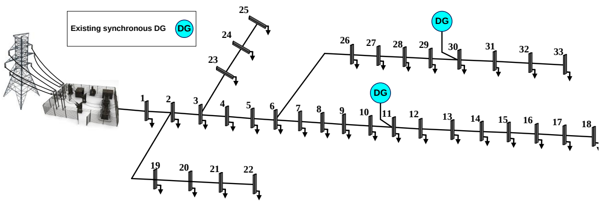


Fig. 1. Single-line diagram of the 33-bus test system.

Table 1. Input parameters for WT, ESS, DG, and network.

Element	Parameter	Value
WT	P_{rated}	750 kW
	V_{cin}	3 m/s
	V_{cout}	25 m/s
	V_{rated}	12 m/s
	$\begin{cases} WT^{Max} = 3 & ;\forall \text{ case } 3 \\ WT^{Max} = 0 & ;\forall \text{ otherwise} \end{cases}$	
ESS	SOC^{Max}	1 MWh
	P^{ESS}_{Max}	0.2 MW
	SOC_0	$\frac{SOC^{Max}}{3}$
	$\begin{cases} ESS^{Max} = 3 & ;\forall \text{ case } 3 \\ ESS^{Max} = 0 & ;\forall \text{ otherwise} \end{cases}$	
DG	S^{DG}_{Max}	500 kW
	PF	0.9
	$\begin{cases} DG^{Max} = 5 & ;\forall \text{ case } 2 \\ DG^{Max} = 2 & ;\forall \text{ otherwise} \end{cases}$	
Network	$I^{Max}_{i,j}$	250 A
	$\Pr^{SUB}$	60 \$/MWhr
	D	365 days/year
	$emc(\$/ton)$	45
	$GE(tons/MWhr)$	0.632
	$DGE(tons/MWhr)$	0.365
	Horizon year	5, 10, 15, 20
	$\begin{cases} V_{i,t,s} = 1 & ;\forall i \in \Omega_{Slack} \\ 0.93 \le V_{i,t,s} \le 1.05 & ;\forall \text{ case } 1 \\ 0.95 \le V_{i,t,s} \le 1.05 & ;\forall \text{ case } 2, \text{case } 3 \end{cases}$	

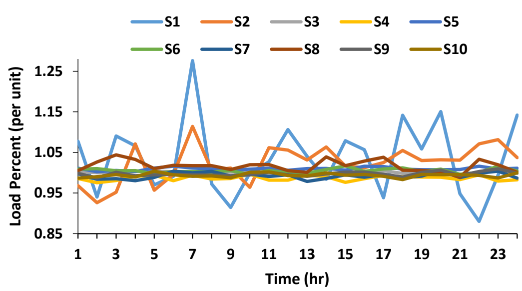


Fig. 2. Uncertainty daily load profile of network.

3. Numerical Study

In order to evaluate the presented approach, its performance has been numerically tested in this part.

Table 2. Specification of candidate DG units.

DG technology	Units' energy capacity (kVA)	Installation cost (\$/kVA)	Operating cost (\$/MWhr)
Gas turbine	500	400	46
Wind turbine	750	800	0

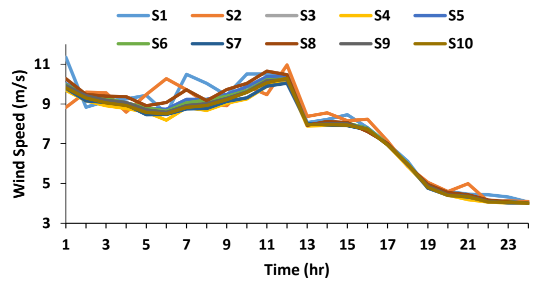


Fig. 3. Input parameters for WT, ESS, DG, and network.

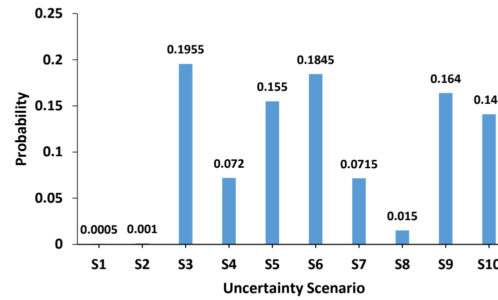


Fig. 4. Probability of each uncertainty scenario.

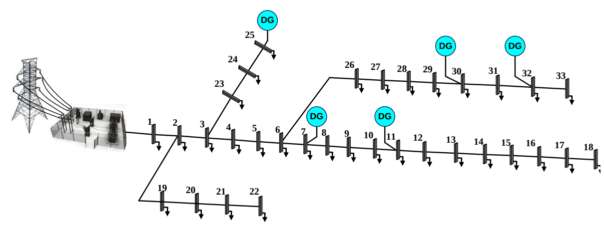


Fig. 5. Network topology after expansion in case 2.

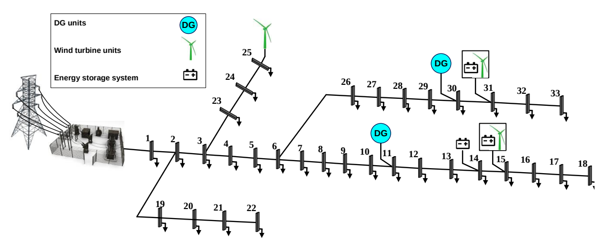


Fig. 6. Network topology after expansion in case 3.

3.1. The test network and problem inputs

The presented model is programmed and implemented in the GAMS software. All the problem formulations are convexified to compose a MIQCP model, and the "GUROBI", as a global optimum solver, is employed for the optimization purpose. As the proposed approach is a convex optimization, it gives a unique and optimum solution without needing to comparing it with meta-heuristic algorithms such as genetic algorithm (GA), particle swarm optimization (PSO), etc.

For a better perception of the solution process of the proposed model, the following procedure can be considered:

Step 1) Import the required data

1-1) Get the distribution system data

- Location of loads and their values

Table 3. Specification of candidate ESS units.

ESS technology	Energy capacity of each unit (MWhr)	Charge/discharge capacity (MW)	Installation cost ($/kWhr)	Efficiency of charge	Efficiency of discharge
Energy storage system	1	0.2	200	0.95	0.9

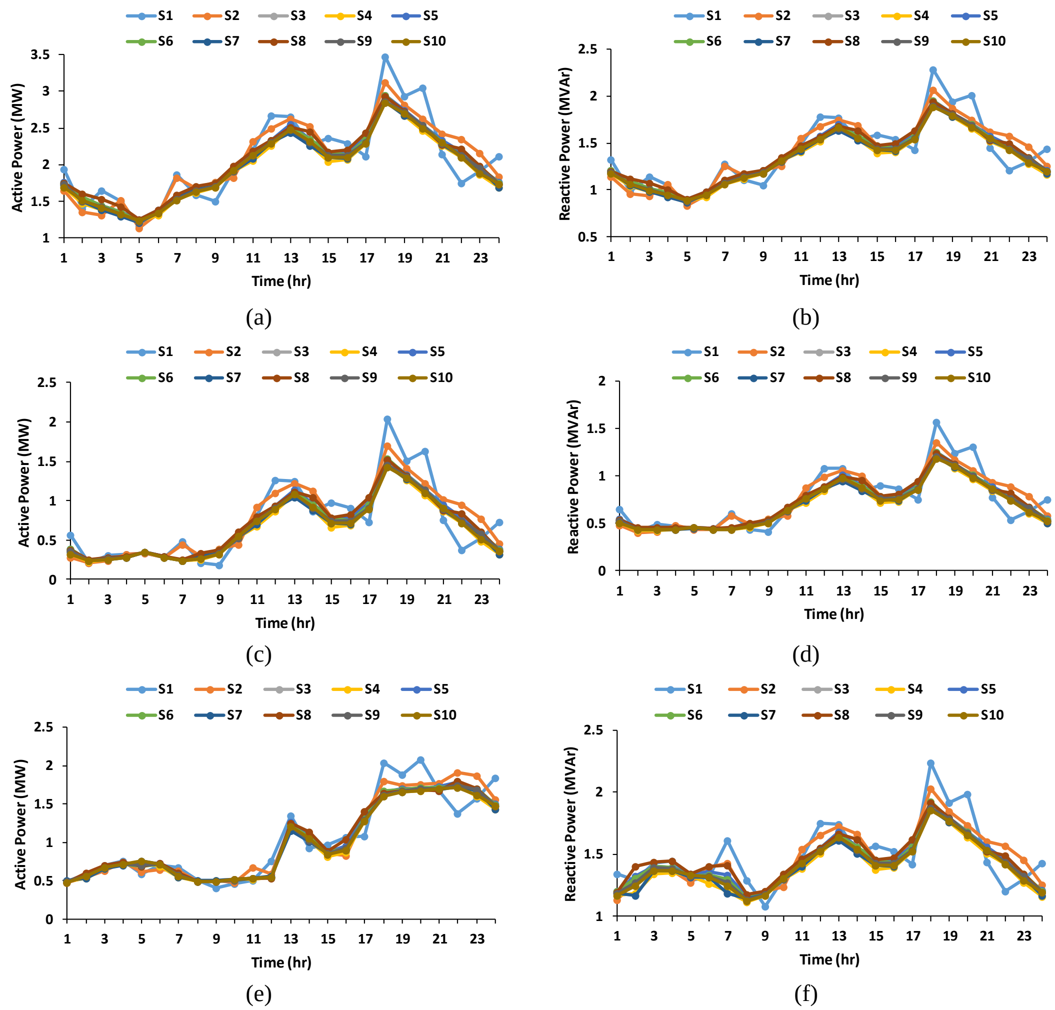


Fig. 7. Active and reactive powers received from the upstream network, (a) and (b): Case 1, (c) and (d): Case 2, (e) and (f): Case 3.

Table 4. Location of DER units.

	Existing DG @ bus	New DG @ bus	New WT @ bus	New ESS @ bus
Case 1	11, 30	—-	—-	—-
Case 2	11, 30	7, 25, 32	—-	—-
Case 3	11, 30	—-	15, 25, 31	14, 15, 31

- Location of existing DG units
- Configuration (route) of lines
- Lines impedances (reactance, resistance)

1-2) Get the synchronous DG data

- Minimum/maximum active/reactive power capacity
- Price of generated power

1-3) Get the wind power generators data

- Rated power
- Rated, cut-in, and cut-out speeds

1-4) Get the loads data

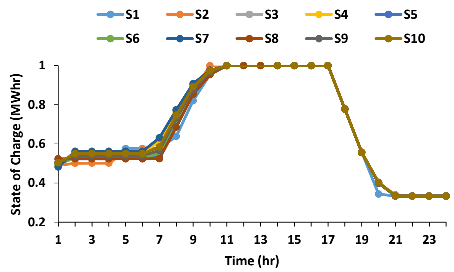
- Peak value of active/reactive powers

Table 5. Results of cost components in three cases.

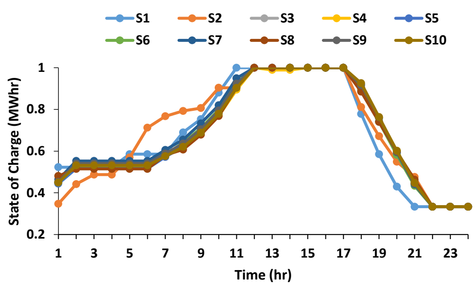
Cost component		Case 1	Case 2	Case 3
IC^{DG} (M$)		0	0.6	0
IC^{WT} (M$)		0	0	1.8
IC^{ESS} (M$)		0	0	0.6
Total installation cost (M$)		0	0.6	2.4
OC_y^{SUB} (M$)	y=5	15.46	6.43	11.32
	y=10	44.34	18.43	32.47
	y=15	75.24	31.27	55.10
	y=20	105.37	43.80	77.16
OC_y^{DG} (M$)	y=5	5.65	13.75	4.57
	y=10	16.19	39.42	13.09
	y=15	27.48	66.89	22.21
	y=20	38.48	93.67	31.11
Total operation cost (M$)	y=5	21.11	20.18	15.89
	y=10	60.53	57.85	45.56
	y=15	102.72	98.16	77.31
	y=20	143.85	137.47	108.27
EMC_y (M$)	y=5	9.70	7.45	5.50
	y=10	27.80	21.38	15.77
	y=15	47.17	36.27	26.76
	y=20	66.06	50.79	37.47
OF_y (M$)	y=5	30.81	28.23	23.79
	y=10	88.34	79.82	63.73
	y=15	149.89	135.03	106.47
	y=20	209.91	188.86	148.15

Table 6. Comparison of profits in three cases.

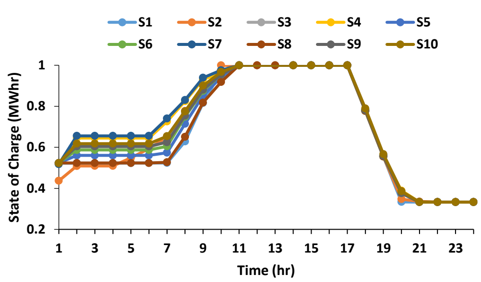
		Profit (in M$ and %)					
		Case 2 VS. Case 1		Case 3 VS. Case 1		Case 3 VS. Case 2	
$\Pr ofit\,(M\$) = OF_y^{Case(\beta)} - OF_y^{Case(\alpha)}$	y=5	2.58	8.37%	7.02	22.78%	4.44	15.73%
	y=10	8.52	9.64%	24.61	27.86%	16.09	20.16%
$\Pr ofit\,(\%) = \frac{OF_y^{Case(\beta)} - OF_y^{Case(\alpha)}}{OF_y^{Case(\beta)}}$	y=15	14.86	9.91%	43.42	28.97%	28.56	21.15%
	7=20	21.05	10.03%	61.76	29.42%	40.71	21.55%



(a): Bus 14

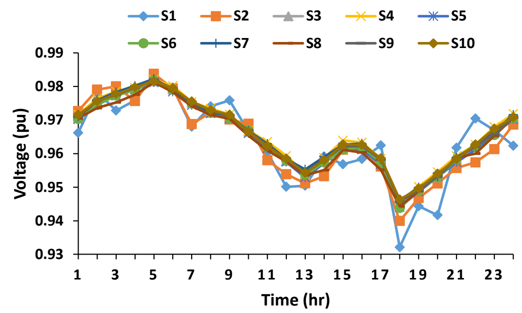


(b): Bus 15

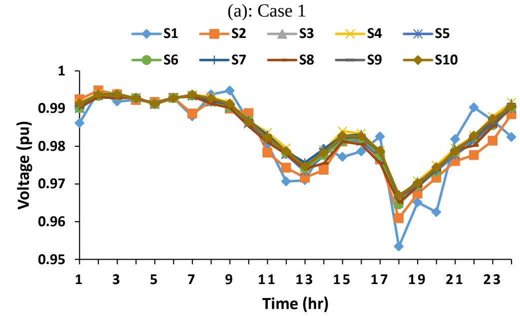


(c): Bus 31

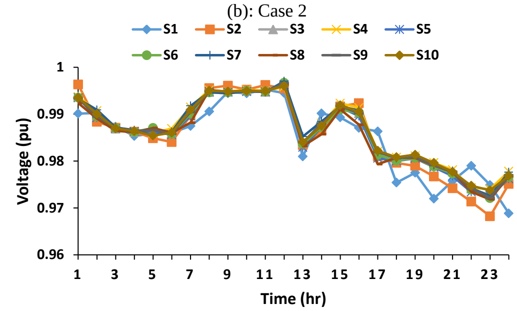
Fig. 8. Energy level of ESS units in case 3 in different buses and uncertainty scenarios.



(a): Case 1



(b): Case 2



(c): Case 3

Fig. 9. Voltage magnitude of bus 18 in three cases under different uncertainty scenarios.

- 24-hour load profile

1-5) Get the weather data

- 24-hour wind speed
- Generation of uncertainty scenarios based on Monte Carlo technique

1-6) Get the ESS units data

- Maximum state of charge capacity
- Maximum charge/discharge rate
- Charge/discharge efficiency

Step 2) Determine the decision variables

2-1) LFB algorithm as convex AC power flow equations is used. The main decision variables include:

- Active/reactive power balance at each bus of the network
- Voltage magnitude of buses
- Active/reactive power generation of DG units
- Active power generation of wind units
- Injected power from the upward grid
- Charge/ discharge scheduling of ESS units

Step 3) Determine the objective function and the problem constraints

3-1) Objective function: sum of generation cost, load shedding cost, and wind curtailment cost

3-2) Constraints:

- Power flow equations
- Minimum/maximum active/reactive power of DG units
- Maximum generation of wind power units
- Maximum allowable power flow through lines
- Voltage limit of buses

Step 4) Set the optimization problem as a MIQCP model and assign a proper solver for the presented model

4-1) Set GUROBI as the MIQCP solver

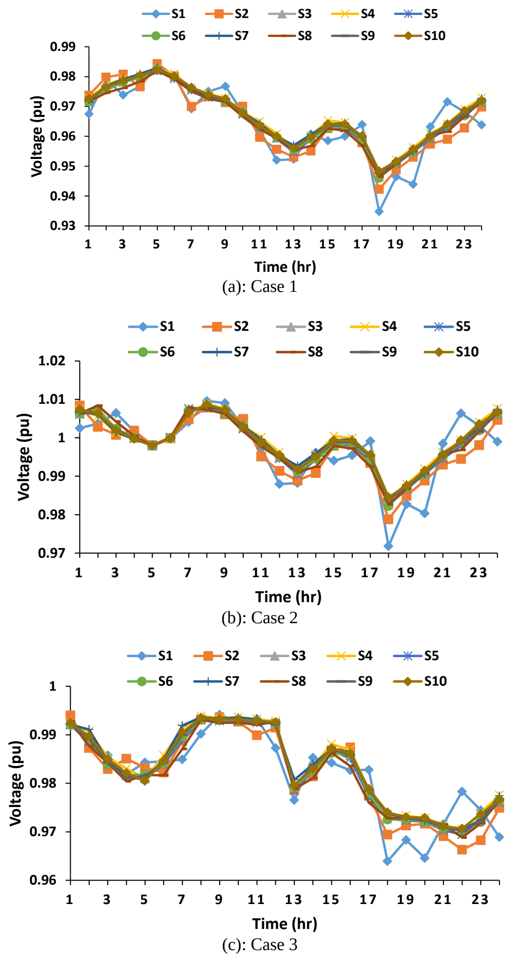


Fig. 10. Voltage magnitude of bus 33 in three cases under different uncertainty scenarios.

Step 5) Adjust the required settings for the model and solver

5-1) Adjust the iteration limit (iterlim= 1000000 in GAMS)

5-2) Adjust maximum time that the solver may run before it terminates (reslim= 1000000 in GAMS)

5-3) Adjust maximum number of nodes to process in the branch and bound tree for MIP problem (nodlim= 1000000 in GAMS)

Step 6) Run the GAMS optimization model and set the software to print the results on an Excel file

The test system, as shown in Fig. 1, is the IEEE 33-bus network [20]. The network is a 12.66kV distribution system with 32 fixed lines in total with radial structure; two synchronous DG units exist in the network before the expansion planning. These two units have been allocated such that the power loss is reduced. The system's total peak load is 3.715MW and 2.3MVAr [20]. The load and line data for this system can be found in [21]. Also, Table 1 prepares the required parameters of the problem. Specification of candidate DGs and ESS units are presented in Tables 2 and 3, respectively [9, 22]. By employing the Monte-Carlo technique, and using hourly mean and standard deviation given in [23] and [24], 1000 uncertainty scenarios of wind speed and load demand are generated, and then, the k-means clustering algorithm is employed to reduce the scenarios to 10 ones. Specifications of the reduced scenarios are given in Figs. 2, 3, and 4.

3.2. Simulation results

In this paper, three simulation cases have been set up to evaluate the impact of power loss and air pollution on distribution network expansion and operation cost, and also the effect of using DER units instead of supplying all of the system loads through upstream network. In order to find out just the explained parameters, the loads will not grow in each horizon year and are fixed as the first year. It is obvious that if each case can become the best solution for this examination, it will be the global answer and it will be more acceptable when the loads are grown in each horizon year. Therefore, in these cases there is no need to change lines and expand the substation. This is another reason not to have load growth. The studied period includes future 5, 10, 15, and 20 years (as horizon years).

A) Case 1

In this case, the network is not expanded, and it is operated for the future horizon years.

B) Case 2

In this case, only new synchronous DG units are installed in the network, and they are optimally allocated. A maximum number of 3 units are allowed to be installed.

C) Case 3

In this case, instead of synchronous DGs, the ESS and WT units are allocated in the network, and the maximum allowed number of ESSs and WTs is 3.

Table 4 presents specification of installed DER units in three cases. As there are two existing DG units at buses 11 and 30, the new installed DER and ESS units are shown in Figs. 5 and 6. As seen, the DER units are placed at appropriate locations in the middle and ending parts of the network to supply the loads and satisfy the constraints.

In Table 5, the output results such as installation cost, operation cost, emission cost, and the total objective function value for each case study is presented. As seen, the cases 3, 2, and 1 have higher investment cost, respectively. The operation cost related to energy purchase from the upward grid has the maximum value in case 1; it is minimum in case 2; and in case 3, the operation cost is more than case 2. The operation cost of DER units is minimum in case 3 and is maximum in case 2. Also, in case 1, the related operation cost is between case 2 and case 3. Due to exploitation of wind turbine and ESS units, there is a cost reduction in case 3 compared to other cases. It can be seen that the total operation cost decreases from case 1 to case 3.

On the other side, nowadays, the global warming and human health have become the most important concerns of mankind. Emission of CO_2 gas, apart from its financial costs, has unfavorable consequences along with destruction of the environment. In this regard, planning for the network infrastructure enhancement is much important for human survival and health of the planet. As shown in Table 5, the use of renewable energy resources and ESS units in case 3 results in less CO_2 emission and lower emission cost. Also, case 2 is better than case 1, as in the presence of DG units, the system needs lower values of energy to be received from the upstream grid. Also, lower power loss is created in distribution system. In other words, the power loss in the network is reduced through reduction of power injection from the upstream network. In the horizon year of 20, the emission cost is reduced by 43.2% and 26.2% in case 3 compared to cases 1 and 2, respectively. The total cost (objective function) is also compared in Table 5. Although case 3 has high installation cost, the total cost in this case has the lowest value as the operation and emission costs are decreased. In other words, in the long-term (horizon year of 20), reduction of operational and emission costs compensates for the increase of installation cost, such that in total, there is a cost reduction of 29.4% and 21.5% in case 3 compared to cases 1 and 2, respectively.

Table 6 compares among profits of three cases in four horizon years. As the horizon year increases, the superiority of the proposed model is more highlighted. This verifies that using renewable energy resources and energy storage systems in the network is more economical than using synchronous DG units in the long-term. Both of these two conditions (case 3 and case 2) are more economical than case 1 in which new DG and DER units are not present.

According to Tables 5 and 6, in case 3, the total installation cost is about 2.4 M$ and the profit of this case compared to case 1 is about 7.02 M$ in the horizon year of 5. Therefore, by installing WTs and ESS units, in the next 5 years, in addition to returning the installation cost, 292.5% of profit is gained compared to the installation cost. Therefore, it is the main purpose of this paper to prove that the installation cost of renewable energy resources and ESS units will be returned in less than 5 years. In fact, due to high power loss cost, emission cost, and energy purchase cost, the DERs installation will be cost-effective and economical. It should be noticed that in case 3, about 60% of the load demand is supplied by DER units. It was assumed that the load demand is not increased. If we consider the load demand growth, the effect of DER installation will be more highlighted. Fig. 7 compares the amount of active and reactive powers received from the upstream network in three cases and in different uncertainty scenarios. It is observed that the injected active and reactive powers to distribution network are increased at the peak load hours to follow the load demand pattern and supply the loads properly. As shown, in case 2, there is a considerable reduction in the injected power, which is due to generation of synchronous DG units. Although in case 3, there is no significant change in power received from the upstream network, the total operation cost has been reduced from 137.47M$ to 108.27$, which is due to scheduling of WT and ESS units. It should be noticed that in case 3, regarding the wind speed variations, the output power of WT units is lower than their rated capacity, but, by an appropriate scheduling of ESS units, it is seen that the power delivered by the upward grid to the distribution system is almost the same as case 2.

In Fig. 8, state of charge (SOC) of ESS units has been illustrated for case 3 in different uncertainty scenarios. As it can be observed, the ESSs are charged from hour 1 to hour 11 reaching to their maximum capacity. From hour 17 to hour 21, they are discharged in accordance with the load increase at these hours, and reach their initial SOC at the last hour of day. Regarding the buses at which the ESS units are installed, the charging and discharging profile of ESSs are different in different uncertainty scenarios. In total, the scheduling of ESS units is in a way that the operation and installation as well as emission costs are decreased.

From the network voltage viewpoint, the three cases have been compared using the voltage magnitude of two sample buses 18 and 33. This comparison can be seen in Figs. 9 and 10 for the whole day. It is obvious that in case 1, the voltages of buses located at the end of feeder drop to values lower than 0.95 per unit (pu) during the peak load hours. This is not favorable for the network operator and loads. However, in cases 2 and 3, the ending buses' voltages are within the acceptable range.

The minimum voltage is occurred at hour 18 for all the uncertainty scenarios. It is seen at this hour, the 5^{th} uncertainty scenario (S5) has the minimum voltage equal to 0.931pu and 0.952pu respectively in cases 1 and 2. This is while for case 3, the minimum voltage is 0.968pu happening at hour 23 in scenario 2 (S2). In total, the voltage profile of the system is improved by employing the DER units despite having lower costs.

4. CONCLUSION

This paper proposed a convex model with a new approach for evaluating the long-term effects of distributed energy resources on supplying the loads of distribution system considering of power loss cost as well as the emission cost. In addition, the installation and operational costs are considered, and the problem uncertainties have been taken into account using scenario-based model incorporating Monte-Carlo and k-means techniques. The proposed model is established as a MIQCP model implemented in the GAMS to find optimal solutions. Different experiments are set up and investigated on the IEEE 33-bus network. The simulations prove the effectiveness of the proposed approach from the viewpoints of cost efficiency as well as emission cost reduction. It is indicated that the installation cost of renewable energy resources and ESS units will be returned in less than 5 years. In fact, due to high power loss cost, emission cost, and cost of purchasing energy from the upward grid, the DERs installation will be cost-effective and economical. As the future work, the total cost reduction and emission reduction can be considered as a multi-objective optimization to find Pareto-optimal solutions. In addition, the effect of network reconfiguration, as a short term planning approach can be investigated to see the possible cost reduction as well as technical improvements.

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