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Multi-objective resilience enhancement program in smart grids during extreme weather conditions

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ABSTRACT

Weather based electrical power outages cover a huge part of consumer interruptions. So, reliable-economical operation of grids during extreme weather conditions is one of challenges for grid operators. In this regard, this paper proposes resilience enhancement programs in order to increase resilience and economic profits in a smart grid. In proposed approach, resilience improvement is done by modeling weather effects on branches outages and then re-scheduling of distributed energy resources and energy storages, load shifting and dynamic reconfiguration of distribution network. In this paper, hourly variation of weather depended failure probabilities are considered. Resilience enhancement programs aim to mitigate effects of events which may cause by extreme weather before fault inception by rescheduling of resources and selecting suitable reconfigurations. Also, reconfiguration isolates damaged parts after fault inception. The objectives in the proposed approach are defined as minimizing operational cost of distribution network and energy not supplied penalty costs from the system operator's viewpoint, as well as, maximizing benefits of energy resources owners by considering weather conditions. A multi-objective optimization algorithm based on genetic algorithm and epsilon constraint method using fuzzy decision maker is employed to choose the best solution from a provided Pareto optimal set. In order to evaluate performance of proposed resilience enhancement programs and its effect, resilience assessment metrics are studied. Various simulations prove the efficiency of proposed model in compare with traditional grid during extreme weather conditions.

1. Introduction

With ever increasing importance of sustainability, operational planning optimization methods are used as solutions for resilience improvement in grids. The abilities of traditional grids are improved by using communication technologies and other advanced technologies gradually. On the other hand, using Distributed Generation (DG), Energy Storages (ESs), Electrical Vehicle (EV) and Demand Response Programs (DRP) in smart grids are inevitable and have increasing tendency [1-3].

Resilience is one of unique concepts of power system studies that attracted the attention in last decade. Different strategies have been suggested to improve resilience of power systems based on optimal planning during normal or emergency conditions [4-6]. These strategies have been designed based on advanced instruments and smart operation. In the most of studies, resilience definitions have been introduced to explain the grid resilience. Unfortunately, events caused by extreme weather could damage grids for an extended time. However, efficiency and impact of reliability methods in most of recent major outages has not been satisfactory during extreme weather conditions. As a result, resilience studies focused on improving grid operation during high risk conditions [7].

Outage forecasting is a key factor for resilience improvement. In [4] a new method is introduced to assess consecutive outages and faults to conquer on complex calculations of analysis in emergency conditions which is based on Mont Carlo simulation. In this regard, [8] proposes a new approach for calculating restoration time for grids after hurricanes. New models have also been developed for prediction of outage duration. In [9], mathematical models for outage forecasting are introduced considering different variables such as wind speed. In [10], outage prediction model is presented which is able to forecast outages during natural hazard events using a number of input parameters. In [11] and [12], different aspects of a network with resilience feature are considered. Fault isolation, fault location detection and reforming of network to the normal state are considered in these investigations. After fault inception, resilient grid detects fault and then primary actions such as fault isolation procedure and etc. will be applied to the grid. Then

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Nomenclature

Abbreviations

$A_j/B_j/C_j$ cost coefficients of active power in DG number j
CT_j^Q cost coefficient of reactive power in DG number j
C_{repair} lines repair cost
$C_{switching}$ switching cost
C_k^{deg} depreciation coefficient for battery number k
$Cost_{R,h}$ energy not supplied penalty cost
DLF_h demand level factor at time interval h
DR_h costumers participation in demand response programs at time interval h
DR^{min}/DR^{max} maximum/minimum limits for participations
$En_{k,h}$ level of stored energy in battery number k at h time interval
En_k^{max}/En_k^{min} maximum/minimum limits for stored energy in battery
ENS_h Energy Not Supplied at h time interval
f_{rate} rate of branches failure (f/km-year)
$ldr_{i,h}$ shifted load after DRP at bus i at demand level h
l_b length of branch b (km)
N_b branches number
N_{bus} Buses Number
N_{DG} DGs number
N_h demand level number
N_k batteries number
N_{load} loads number
N_{switch} switches number
N_{wind} number of events caused by storm
N_{WT} wind turbines number
$P_{k,h}^{charge}/P_{k,h}^{discharge}$ k^{th} battery charging/discharging at h demand level
$P_k^{charge,min}/P_k^{discharge,max}$ limits on the charging/discharging
$P_{i,base}^D/Q_{i,base}^D$ active/reactive base load of bus i
$P_{i,h}^{DG}/Q_{i,h}^{DG}$ active/reactive power sold by DG connected to bus i at demand level h
$P_{i,h}^{DR}$ load demand after DRP at bus i at demand level h
$P_{min}^{DG}/P_{max}^{DG}$ minimum/maximum limits for DG power injection
$P_{res,h}$ not restored loads after fault at demand level h
P_h^{us}/Q_h^{us} active/reactive power sold by substation at demand level h
$P_{us}^{min}/P_{us}^{max}$ minimum/maximum limits for substation power injection
$P_{j,h}^{WTG}$ active power injected by Wind turbine number j at demand level h
PLF_h price level factor at time period h
$Q_{min}^{DG}/Q_{max}^{DG}$ minimum/maximum limits for DG reactive power injection
$Q_{min}^{us}/Q_{max}^{us}$ minimum/maximum limits for substation reactive power
$S_{ij,h}$ power flow through line connected between nodes i and j at demand level h
S_{ij}^{max} maximum power flow through the line connected between nodes i and j
t_{res} restoration time
$V_{i,h}/\delta_{i,h}$ magnitude/angle of voltage at i^{th} bus and h^{th} hour
V_i^{min}/V_i^{max} minimum/maximum limits for voltage
W_{Speed} wind speed in each time interval
α_{ij} binary variable set to 1 if there is a connection between bus number i and j and to 0 otherwise
$\beta_{k,h}^{charge}/\beta_{k,h}^{discharge}$ binary variables depicting charge or discharge status of k^{th} battery
$\eta_k^{charge}/\eta_k^{discharge}$ charging/discharging efficiency for battery number k
ρ_{base} base price for each MWh
ρ_h modified price for each MWh
ρ_h^Q VAR price for each MVarh
ρ_P ENS penalty cost for each MWh
ρ_{sell} energy selling price for each MWh
ρ_{sell}^{WTG} WTG power price for each MWh

different reforming strategies follow the reconfiguration activities regarding to defined or existed aims. Shaded loads are restored in the last step. In [13] in addition to reconfiguration, other resources scheduling is studied in the framework of multi- objective optimization to minimize Energy Not Supplied (ENS).

In [14] various models for network planning under normal and emergency conditions are studied. In [15] another risk-based network planning considering grid resiliency during natural disasters is proposed, in which cost reduction as well as availability improvement are considered. In [16] a stochastic programing is introduced to set an optimal scheduling for inspection, damage evaluation, and repairing in post-failure restoration. In [17] proposed approach includes optimization algorithm to minimize outages duration for each customer. Regarding infrastructure of grid, [17] studies grid resilience based on the distribution network infrastructure and its interaction with natural events. Results show that infrastructure can be effective on outage duration and number of outages. In [18] a comprehensive method is introduced to create resilient cities which are able to withstand disasters. The main contributions on that paper are discussions about importance of resilience, and the ways to improve it. In [19], an approach is presented for evaluation of the infrastructure behaviour, during natural hazard events. Similar researches with focus on resilience-oriented designs have been done in [20-22], which propose structural upgrades and backup DG units. In [20], the reconfiguration issue and its impact on the quality of consumers welfare related to operation affairs are considered. In [21], the graph method and graph dissection are employed for optimal planning of sub-networks using distributed generators and energy storages in which, the main goal is enhancement of the power quality and self-healing. In [23] outages management and network repair time optimization are applied using reconfiguration. In most of researches, there is not a dynamic risk evaluation for re-scheduling and operational planning by considering probabilistic nature of weather-based outages. Also, in some of them, authors focused on improving economic or resilience of grids individually. However, it is clear that both economic and resilient operation of grid are important during high risk times.

In [24], for resilience improvement, the issue of switches allocation is solved to minimize users' outage cost and the switch installation cost by numerical calculations. In that paper, profit and loss analysis in long-term are considered for optimal operation from a distribution network operator viewpoint by using reconfiguration. Load uncertainty and network capability improvement through outage reduction are some features of that research. In [25], cooperative employment of different resources and technologies in grid and reconfiguration are studied. The reliability improvement and operation cost minimization with hourly reconfiguration are the aims of modelling and problem solving. Also, a method in [26] is adopted by considering renewable power resources. In [27], the simultaneous optimization of operation and investment was regarded. In this study load growth is satisfied using distributed generation in the planning level and reconfiguration. These investigations show that reconfiguration as an old approach in power distribution networks literature, has still high importance in the presence of loads and new power resources. So, it will be an effective tool in operation with various goals. It seems that with the movement of traditional networks towards exploited smarter ones, this issue is still important. So, real time reconfiguration will be a vital part of resilience improvement in smart grids, where fault location, its isolation from other parts of grid with minimum load shedding and reenergizing in minimum time are main challenges. In initial steps, reliability indices would be used to evaluate resilience [28].

In [29] an approach is proposed to improve resilience of transmission lines. The main idea of this research is based on combined investment on capacity expansion and switch installation that increase efficiency of transmission lines for long-term planning and short-term operation. Also, considering both mentioned actions decrease investment budget and improves resilience of transmission lines efficiently. In [30] a two steps resilient outage management scheme is presented based on scheduling of energy resources in microgrids and control of power transfer in tie lines. In that work, optimal use of resources capacity in all microgrids is studied to feed loads during emergency conditions. However, this study focused on optimal resources management to enhance microgrids resilience, but the proposed outage management system is scenario-based and a pre-determined time is considered to remove fault after fault inception. Also, profits of DG owners in microgrids, cooperated with distribution network operator, have not been considered. A similar research is discussed in [31] to evaluate impact of extreme weather condition on power systems. The output of that research paper is a novel risk-based defensive islanding algorithm that aims to decrease side effects of events which may occur during extreme weather condition. This goes beyond the infrastructure-based measures that are traditionally used as a defence to severe weather. The resilience assessment procedure considers probability of weather-dependent fault of infrastructures. In [32], a method is introduced based on optimal allocation of wind turbine generators, ES and EV charging stations by considering DRP. The proposed method in [32] takes advantage of hourly reconfiguration to decrease total energy purchase costs. However, some specific contingencies are considered in that research and resilience of grid is evaluated for three certain events. In general, resilience must cover dynamic risk probability during operational or planning time interval by using both energy resource rescheduling and reconfiguration. But in that research just reconfiguration improves resilience of grid by isolating damaged parts.

To summarize the reviewed studies, the following research gaps can be classified:

- In literature review, few studies are paid to the benefit sharing between DISCO and private sector. It is clear that without fair profit sharing and economic profits for private sector, there will be no investment on electric vehicles charge station (EVCS) or other resources.
- A few studies have analysed a trade-off between opposite direct objective functions. Indeed, aforementioned objectives have been optimized only from one viewpoint.
- Lack of a suitable model is visible in most studies to optimize important objective functions simultaneously such as: energy cost, battery degradation, grid net exchange and ENS cost and etc.
- Another drawback of literature review is the lack of attention to network resilience while it is one of the most important features of the smart grid. One of the profits of employing EVCS, along with its technical and economic advantages, is the network resilience improvement, which seems to be a challenging drawback.

The main aim of this paper is to propose a comprehensive model to investigate network behavior in undesirable weather conditions. The proposed method demonstrates that how smart operation could improve economic operation and resilience of network against outages which are resulted from probabilistic events in determined time interval. In brief, the innovations of this paper can be summarized as follows:

- It evaluates behaviour of smart grids during extreme weather condition and shows that how a resilient grid feels risk of outages and reschedules operational planning in order to pass certain time intervals with high probability of outages.
- It proposes a two-objective optimization model for resilient grid that can balance risk and benefits on a reasonable manner namely Resilience Enhancement Program (REP).
- It proposes a method which can be employed in smart systems with high switching options and dispatchable resources during extreme weather conditions.
- Modelling the effect of wind speed in operational planning, reconfigurations and lines outage rate. Additionally, the analyses are discussed based on wind correlation and outages.

The rest of this paper is organized as follows: The proposed model for REP is presented in Section 2. Mathematical formulation of model is presented in Section 3. Simulations and results are presented and analyzed in Section 4. Finally, conclusions are presented in Section 5.

2. Resilient operational planning

A resilient grid has features such as predication, learning, adaption and recovery after a disruptive event [9]. The resilience improvement could be done through predictive actions and operating measures. Various strategies and operational planning should be considered to increase the flexibility of grids in extreme weather condition. It is obvious that the relation between resilience and actions depends on the weather condition and planning of DGs, loads and ESs. In this paper, rescheduling and reconfiguration along using above mentioned technologies for resilience improvement is called Resilience Enhancement Program (REP). The purpose of operational planning in these conditions is to decrease impact of probabilistic events on outages. It is postulated that during this planning; the consumption of electricity power could be controlled, the required reconfiguration could be done, DGs and ESs scheduling could be reviewed and totally the Distribution Company Operator (DISCO) should minimize side effects of faults in the worst condition. On other hand, DG-ES owners must earn their share of profits obtained by cooperation. Meanwhile, using renewable resources is one of the characteristics of novel energy networks. This means considering uncertainties of these resources will affect and complicate resources scheduling and demand side programming in this circumstance.

It is obvious that for DISCO, both economic and secure operation are important. Reliability and resilience improvements require investment on infrastructure or change in operational planning that leads to solution far from pure economical operation. In traditional methods, reliability improvement focuses on most possible events, so, a set of reinforcements and operational planning approach are resulted for reliability enhancement. In other words, reliability improvement leads to fix solutions for a long time framework. On other hand, it is proved that some rare weather conditions may cause outages that reliability studies do not consider them in solutions for ENS reduction, because they have low occurrence probability. In this paper, by forecasting weather condition and using outages data caused by weather condition, an adaptive short time operational planning is created based on probabilities of possible events. The key feature of the proposed adaptive operational planning is that content of possible events are totally different from reliability studies and the considered faults may be incepted by extreme weather condition. In other words, in reliability enhancement (both in infrastructures and operational planning), extreme weather condition has a little weight due to its scarce nature. However, in resilience enhancement during extreme weather condition, operational planning is different. It is clear that changes in operational planning from economic viewpoint to resilience enhancement one, reduces profits for DISCO. In this compromise, probability of events which may be caused by extreme weather condition (that they are not involved in traditional reliability studies) specify balance of economic and resilient operation. In this way, gained profits by ENS penalty cost reduction during high risk times and amount of extra operational cost caused by changing in traditional operational planning should be considered in calculations. As we know, increase in operation cost due to resilience improvement, could lead to profit increment of DISCO and private owners in long-term, by improvement in resilience of grid and reduction of outages costs. In other words, probabilistic assessment of operational planning changes scheduling from economical state to compound state of economical and resilient. In this regard, optimal operation is guaranteed by using DRP, DG units dispatch and reconfiguration during extreme conditions.

3. Mathematical formulation and models

The proposed model in this paper is based on consumer and DG-ES owners (DGO) cooperation with distribution network operator (DISCO). In suggested optimization model the profits of both DGO and DISCO are considered as objective functions which must be maximized during daily operational planning. In this model, branches outages and output of wind turbines are dependent on weather conditions. A schematic of proposed method including input data, priority of steps and final outputs are presented in Fig. 1.

As shown in Fig. 1 at the first level, the loads (regarding relations (1)–(3) in Section 3.1), different topologies based on reconfiguration of existing switches in the grid and different weather conditions are considered as the inputs of the model. In the next level, in different combinations of demand levels, weather conditions and grid topologies, the proposed programming model in Sections 3.2 and 3.3 is employed to obtain real operation cost including energy purchase price from upstream grid and ENS penalty cost. Note that the considered ENS penalty cost in objective function (relation (10)), is calculated based on formulation (5). As it is possible that demand levels at each time interval change due to operational planning and DRP output results, in third level best topology with minimum ENS penalty cost is selected. Moreover, a modified price which reflects ENS penalty cost and upstream grid price will be calculated based on relation (4) in this level. The updated price and the selected topology will be employed in fourth level to determine the final optimal operational planning. In fact, the updated price is used as a reference price for DISCO to encourage private sector to cooperate in operational planning during high risk time intervals. It is worthy to note that in all abovementioned levels, a weather-based model for lines outage (details presented in Section 3.5) is employed to calculate the ENS penalty cost. In order to verify the efficiency of the proposed model in resilience enhancement, the output results of the model are used to calculate a set of resilience assessment indices. These indices are introduced in Section 3.4.

3.1. Models for demand, electricity price and DRP

Daily load variations could be modelled by multiplying two parameters. The first parameter is peak load ($P^D_{i,max}, Q^D_{i,max}$). Each hour of day is defined as one demand level, so there will be 24 demand levels that are shown with N_h. The second parameter is demand level (DLF_h) which defines the quantity of predicted "load to peak load coefficient" in each demand level and changes from 0 to 1. Hence, i^{th} bus demand in the h^{th} load level is calculated as follows:

$$\boldsymbol{P^D_{i,h}} = \boldsymbol{P^D_{i,base}} \times \boldsymbol{DLF_h} \tag{1}$$

$$\boldsymbol{Q^D_{i,h}} = \boldsymbol{Q^D_{i,base}} \times \boldsymbol{DLF_h} \tag{2}$$

$$\boldsymbol{S^D_{i,h}} = \boldsymbol{P^D_{i,h}} + \boldsymbol{jQ^D_{i,h}} \tag{3}$$

The price of purchased power from upstream grid is determined by market price. This quantity changes in each demand level. However, the real price for DISCO in each hour includes costs of purchasing energy from upper network and probabilistic costs of outages in each hour. So, the real cost of network (ρ_h) for each hour including both determined and probabilistic costs could be shown as follows:

$$\rho_h = \frac{\boldsymbol{\rho_{base}.PLF_h + \rho_P.ENS_h}}{\boldsymbol{PLF_h}} \tag{4}$$

Equation (4) is used as a signal in the administration of REP, because this cost includes both operation and outage costs. Features such as outage rate per each kilometre and the length of network line has impact on the numbers of outage lines and consequently influences the amount of ENS. The amount of ENS penalty cost is obtained as follows:

$$\mathrm{Cost}_{R,h} = \sum\nolimits_{b=1}^{N_b} f_{rate}.l_b.\rho_p.\left(\sum\nolimits_{re=1}^{N_{bus}} P_{res,h}.t_{res}\right) + C_{repair} \tag{5}$$

Equation (5) consists two parts. The first part is depended on outages penalty cost for DISCO. Weather condition may change failure rate of lines and repair time [26]. The other part is depended on repair crew and materials which are used to remove failure. The proposed method can reduce failure rate by using dynamic reconfiguration and reduction of load amount in high risk times. On the other hand, DISCO uses DRP to decrease operational costs by shifting consumer's load consumption peak hours to low load ones. Time of use method is used in this paper to apply DRP. It is essential to mention that in this study it is postulated that customers only could change a limited capacity of their demands. As shown in Fig. 2, demand for each bus can be divided to two amounts consisting fix load and transferred load as shown in Equation (6). Fix load for each bus is not shiftable and consist majority of demand. It is shown in Equation (7). In other side transferable load value would be positive, negative or zero when demand in certain time interval is increased, decreased or not changed by DRP. Also, the summation of load transfers must be equal by zero as mentioned in Equation (8). It is

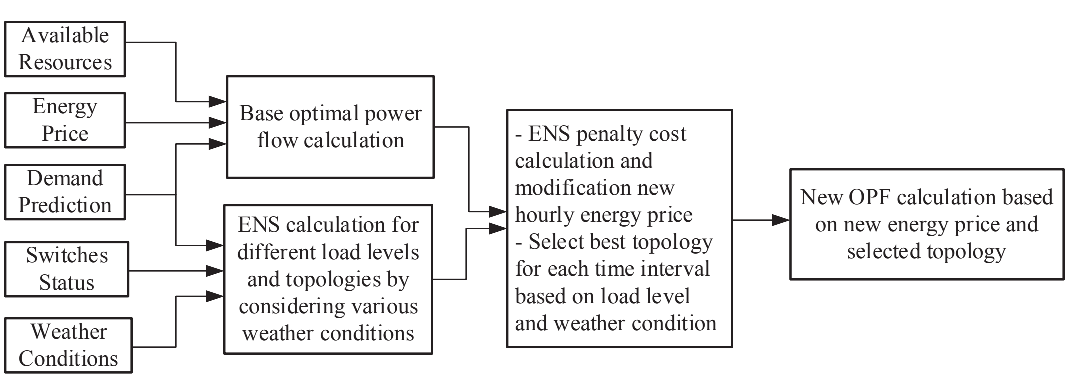

Fig. 1. Schematic of proposed method.

supposed that only ±15% of total load participate in demand response (Equation (9)). So DRP model is mathematically defined as follows:

$$P_{i,h}^{DR} = P_{i,h}^{D} + ldr_{i,h} \tag{6}$$

$$ldr_{i,h} = DR_h \times P_{i,h}^{D} \tag{7}$$

$$\sum_{h=1}^{24} ldr_{i,h} = 0 \tag{8}$$

$$DR^{min} \le DR_h \le DR^{max} \tag{9}$$

It is assumed that loads will be shifted at a fixed power factor. Equation (9) limits the increasing or decreasing in demand in each time interval. Additionally, it is assumed that the quantity of load transfer in all buses will be fixed precent. It is assumed that in all possible reconfiguration, grid remains radial and all buses will be connected. Also, maximum number of topologies is depended on number of switches.

3.2. Objective function

DISCO has the ability to exchange energy with upper networks and also with DG Owners (DGOs). The first objective function in the short-term operational planning aims to maximize energy profit during next 24h for DISCO. Equation (10) expresses profit of DISCO mathematically.

$$OF_1 = \sum_{t=1}^{N_h} \left\{ \begin{array}{l} \sum_{i=1}^{N_{load}} \rho_{sell}.P_{i,h}^{DR} + \sum_{i=1}^{N_k} \rho_{sell}.P_{k,h}^{charge} - \mathrm{Cost}_{R\,h,s} - \rho_{base}.PLF_h.P_h^{us} \\ -\sum_{j=1}^{N_{WT}} \rho_{sell}^{WTG}.P_{j,h}^{WTG} - \sum_{j=1}^{N_{DG}} \rho_h^{Q}.Q_{j,h}^{DG} - \sum_{j=1}^{N_{DG}} \rho_h.\left(P_{j,h}^{DG} + P_{k,h}^{discharge}\right) \end{array} \right\} \tag{10}$$

In equation (10), the first and second terms are the revenues of sold energy to consumers by DISCO. It is assumed that price of reactive power injected by upstream network is negligible. The third phrase is the occurred outage costs of network. As a result, the fourth term is purchased power cost from upstream network or energy market in which the power quantity depends on market electricity price. When $P_{h,s}^{us}$ is negative, it means the grid sells energy to upstream grid. Finally, the three last phrases express the purchased power cost from owners of DG resources. Note that, it is assumed that reconfiguration cost is negligible due to using existing remote switches.

On the other hand, profit of DGO is achieved from selling energy to network and investment on storages. The price of sold energy by DGO depends on the signal price provided by DISCO. The profit function of DGO is formulated as (11):

$$OF_2 = \sum_{t=1}^{N_h} \left\{ \begin{array}{l} \sum_{j=1}^{N_{DG}} \rho_h.P_{j,h}^{DG} + \sum_{j=1}^{N_{DG}} \rho_h.Q_{j,h}^{DG} + \sum_{j=1}^{N_{WT}} \rho_{sell}^{WTG}.P_{j,h}^{WTG} + \sum_{k=1}^{N_k} \rho_h.P_{k,h}^{discharge} \\ -\sum_{k=1}^{N_k} \rho_{sell}.P_{k,h}^{charge} - C_k^{deg}\left(\sum_{k=1}^{N_k} \frac{P_{k,h}^{discharge}}{\eta_k^{discharge}} + \eta_k^{charge}.P_{k,h}^{charge}\right) \\ -\sum_{j=1}^{N_{DG}} \left(A_j {P_{j,h}^{DG}}^2 + B_j P_{j,h}^{DG} + C_j\right) - \sum_{j=1}^{N_{DG}} Q_{j,h}^{DG}.CT_j^{Q} \end{array} \right. \tag{11}$$

In this formulation; first to third phrases are the revenues of DGO from selling energy, the fourth one indicates the revenue of DGO from discharging energy storages, the fifth is the energy cost of charging energy storages which are considered as consumers in network, the sixth phrase is the indicator of ES depreciation cost and finally two last phrases are the operation costs of distributed resources for active and reactive power generation. It is worth noting that the owners of distributed generation units and energy storages are assumed same in this paper.

3.3. Constraints

Active power and reactive power balance equations for each hour are shown as follows:

$$P_h^{us} + \sum_{i=1}^{N_{DG}} P_{i,h}^{DG} + \sum_{i=1}^{N_{WT}} P_{i,h}^{WTG} - \sum_{i=1}^{N_{load}} P_{i,h}^{DR} + \sum_{k=1}^{N_k}\left(P_{k,h}^{discharge} - P_{k,h}^{charge}\right) = V_{i,h}\sum_j V_{j,h}(G_{ij}cos\delta_{i,h} + B_{ij}sin\delta_{j,h}) \tag{12}$$

$$Q_h^{us} + \sum_{i=1}^{N_{DG}} Q_{i,h}^{DG} + \sum_{i=1}^{N_{WT}} Q_{i,h}^{WTG} - \sum_{i=1}^{N_{load}} Q_{i,h}^{DR} = V_{i,h}\sum_j V_{j,h}(G_{ij}cos\delta_{i,h} - B_{ij}sin\delta_{j,h}) \tag{13}$$

The limitations for active and reactive power generation of each DG units including WTG and upstream grid are considered as follow:

$$P_{us}^{min} \le P_h^{us} \le P_{us}^{max} \tag{14}$$

$$Q_{min}^{us} \le Q_h^{us} \le Q_{max}^{us} \tag{15}$$

$$P_{min}^{DG} \le P_{i,h}^{DG} \le P_{max}^{DG} \tag{16}$$

$$Q_{min}^{DG} \le Q_{i,h}^{DG} \le Q_{max}^{DG} \tag{17}$$

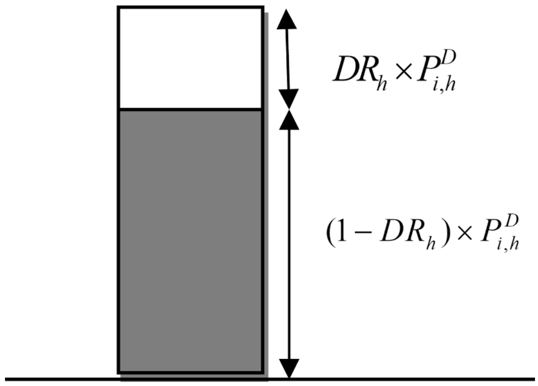

Fig. 2. Load shifting in demand response.

$$0 \le S_{ij,h} \le S_{ij}^{max} \tag{18}$$

Bus voltage must be limited to its permissible ranges.

$$V_i^{min} \le V_{i,h} \le V_i^{max} \tag{19}$$

Equations (20) and (23) show the charge limitation, ES charge and the amount of saveable energy in ES. In this study the saving level of ES in the end of planning is considered equal with primary energy level. Provision (22) expresses that ES could not be charged or discharged simultaneously. The dynamical energy of ES is expressed as equation (23).

$$0 \le P_{k,h}^{charge} \le \beta_{k,h}^{charge}.P_k^{charge,max}$$

$$0 \le P_{k,h}^{discharge} \le \beta_{k,h}^{discharge}.P_k^{discharge,max} \tag{20}$$

$$En_k^{min} \le En_{k,h} \le En_k^{max} \tag{21}$$

$$\beta_{k,h}^{charge} + \beta_{k,h}^{discharge} = 1 \tag{22}$$

$$En_{k,h+1} = En_{k,h} + (\eta_k^{charge} \times P_{k,h}^{charge} - \frac{P_{k,h}^{discharge}}{\eta_k^{discharge}}) \tag{23}$$

3.4. Resilience evaluation metrics

In this Paper, the main idea of proposed method based on REP is operational cost and outages minimization regarding extreme weather condition. In order to prove the effectiveness of proposed method, it is necessary to use suitable metrics to evaluate smart grid resilience. There are various metrics to evaluate system resilience. In this paper, **ΦΛΕΠ** metrics which introduced in [33] are used. Grids might operate in various phases during extreme weather condition as shown in Fig. 3. Proposed method can reduce side effects of events caused by high wind speeds by employing rescheduling of resources, load shifting and proper dynamic reconfiguration. Also, it is possible that in post contingency condition, reconfiguration restores some or total loads by isolating damaged lines. In other words, the total time of outages will be reduced for some faults whom can be isolated with reconfiguration. Various phases of grid state in [33] are presented by the resilience trapezoid model. This model consists three different phases includes, disturbance phases (Φ and Λ–metrics), post-disturbance phases (Ε-metric) and restorative phases (Π-metric). **ΦΛΕΠ** metrics would be defined to the operational R_{pdo} and infrastructure R_{pdi}resilience. Mathematical expression and measuring units for **ΦΛΕΠ** metrics are shown in Table 1 [33].

3.5. Outage model

Results of different researches show that extreme weather conditions (Tornado) are the main reason for more than half of faults inception [34]. In order to evaluate how a resilience grid modifies operational scheduling by considering weather conditions, outages are distinguished into two classes. In the first class, outages with non-weather caused reasons are modelled by a constant interruption value. In the second class, weather-caused faults are considered. In order to have a proper analysis to evaluate weather condition effect on outage rate, the faults mentioned in the second class are modelled by correlations as presented in [34]. Unfortunately, standard distribution test systems don't have weather-caused events data, so, real normalized data is used in simulations in order to evaluate resilience grid behaviour during different

Table 1
Metrics for operational and infrastructure [33].

Metric	Mathematical Expression		Measuring Unit	
	Operational	Infrastructure	Operational	Infrastructure
Φ	$\frac{R_{pdo} - R_{0o}}{t_{ee} - t_{oe}}$	$\frac{R_{pdi} - R_{0i}}{t_{ee} - t_{oe}}$	MW/hour	Number of lines tripped/hours
Λ	$R_{0o} - R_{pdo}$	$R_{0i} - R_{pdi}$	MW	Number of lines tripped
E	$t_{or} - t_{ee}$	$t_{ir} - t_{ee}$	Hours	Hours
Π	$\frac{R_{0o} - R_{pdo}}{T_{or} - t_{or}}$	$\frac{R_{0i} - R_{pdi}}{T_{ir} - t_{ir}}$	MW/hour	Number of lines restored/hour

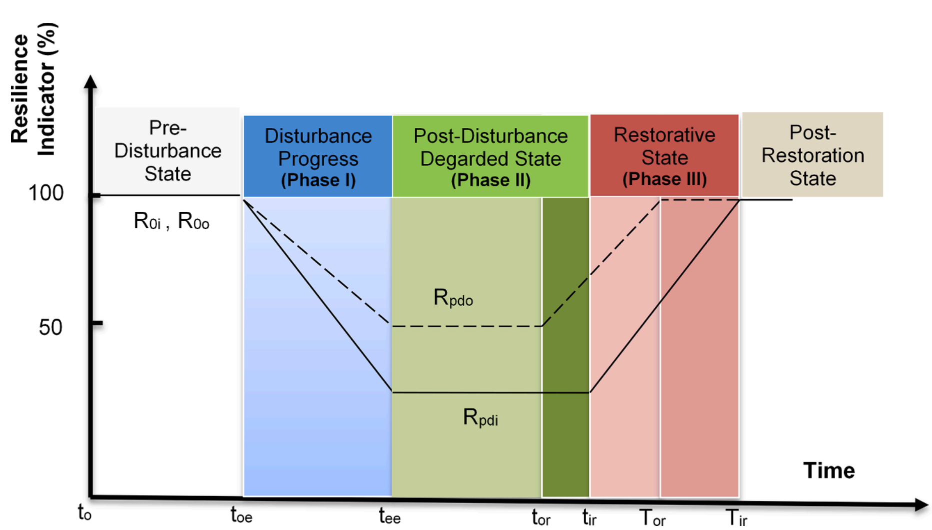

Fig. 3. Resilience indicator change during fault inception [33].

weather conditions. In [34] correlation between events and wind speed for short-time intervals is introduced by using (24).

$$N_{wind} = 0.0012W_{speed}^{2} - 0.0131W_{speed} \tag{24}$$

In above equation, N_{wind} and W are the outages number caused by high speed winds and wind speed. In this paper, for each time interval the medium quantity of wind is used. It is assumed that average wind speed probability could be predicted in one-hour time intervals. In this paper, a fix amount for probability of each branch is considered to model outages caused by various reasons and a variable outage rate related to wind speed is added to obtain total probability of outage for each branch. Wind speed affects WTG power generation as it affects number of outages. It is clear that wind flow patterns and wind speed profiles changes by time and it is possible to estimate some wind patterns for each area. Repair team usually looking for damaged branches and when they found it, they start to solve problem. Repair time depends on event type but it is visible that required time in bad weather conditions is also more than normal weather conditions [34]. It is assumed that in normal conditions average repair time is 4 h and during extreme weather conditions average of repair times is 6 h in simulated test system [35]. So, change in weather conditions affects outage rate, repair time and in sequence ENS value.

3.6. Problem solution method

In this article, the ε-constraint method is used based on [17] regarding different objective functions and existing provision to solve multi- objective mathematical problem. In order to select the best solution, (Fuzzy Decision Maker) FDM method is used. The FDM provides Pareto solutions through all existence solutions by considering wind speed effect on signal price (Equations (4) and (5)). In this study, the minimized- maximized approach was used to compromise existing optimization state.

The optimal topology of grid for each hour is implemented by wind speed, demand level and time of day. Reconfiguration in each time interval is selected with genetic algorithm (GA) and then results are sent to multi- objective mathematical problem. The purpose of GA method is to decrease ENS cost and energy loss, because these parameters influence real costs of network operation. After reconfiguration for each time interval, optimal plan regarding reformed energy price (Equation (4)) is implemented to balance resilience and economical functions. It is necessary to mention that the occurrence of extreme weather condition does not mean outage occurrence in network but probabilistically the lines outage rate strongly depends on weather condition and hence by worsening weather conditions the network proceeds to enhance resilience. This action decreases network profit corresponded with intensity of danger of extreme weather condition, but as it will show in the next section, the grid resilience and long-term profit will be improved by REP.

Table 2
Pareto optimal solutions for studied cases.

Case #	Solution #	DISCO ($)	DGO ($)	ENS cost ($)
Case 1	1	6762	317	3154
	13	6620	484	3128
	20	6306	581	3119
Case 2	1	7204	277	2895
	12	7014	466	2879
	20	6694	576	2862
Case 3	1	7524	268	2530
	13	7352	451	2494
	20	7160	556	2490
Case 4	1	7739	270	1985
	13	7612	376	1971
	20	7384	447	1969

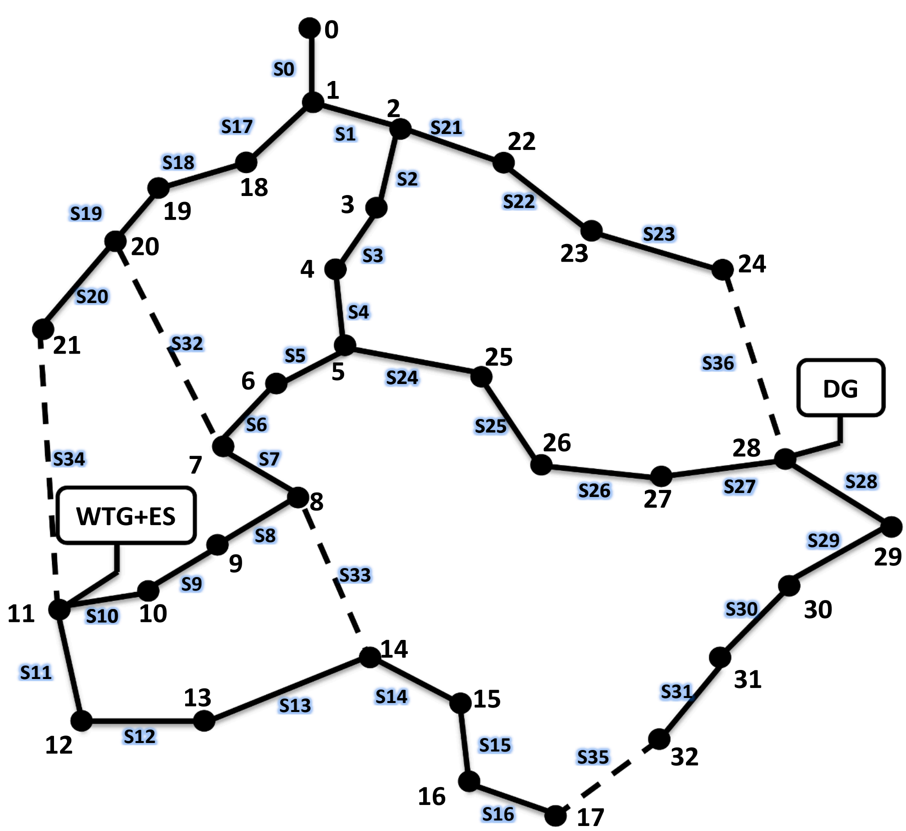

Fig. 4. Simulated test system.

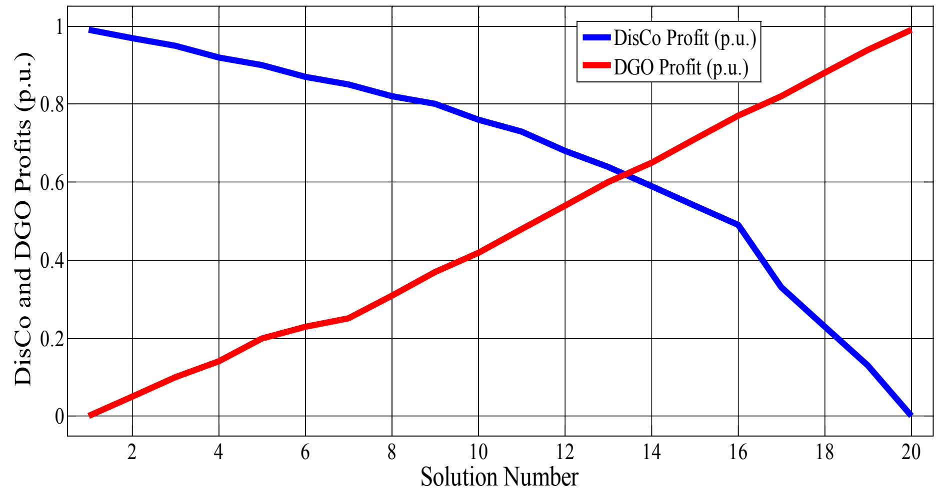

Fig. 5. Solution results used in min-max method for Case 4.

4. Simulation results

The suggested test system for proposed method is 33-bus test system shown in Fig. 4. In this network five switches were considered. The required data is derived from [29] with some modifications to study the current issue. DG and wind turbine with 1 megawatt capacities are located in buses 11 and 28. The ES unit with the capacity of 0.6 megawatt-hours is located in bus 11 with the charged and discharged rate of 300 kW. The minimum and maximum of saved energy in this unit is 100 kW in hour and 600 kW, respectively. The time step for operational planning is determined one hour. In this paper, value of ENS is considered as resilience index.

In order to show the impacts of proposed short-term planning, the following cases are studied:

Case 1: operational planning without considering DR and reconfiguration
Case 2: operational planning with reconfiguration and without DR
Case 3: operational planning regarding DR and without reconfiguration
Case 4: operational planning regarding DR and reconfiguration

In all cases weather condition is assumed the same and during a 4-hours course (13–17) in comparison to other hours will have inappropriate hours due to possibility of tornado.

In all cases, the effects of extreme weather condition in operational planning and the penalty cost of ENS for each time interval are calculated. Also, the numbers of outages and the time of repair for each case were considered same. Network optimal reconfiguration for each wind speed regarding demand level and energy price is calculated by GA and then it is used for operational planning optimization. In other word, in operational planning, resources planning and flexible loads are achieved by using obtained search table from first stage of optimization. In all cases, the sums of Pareto solutions are achieved for network. The obtained profit for DISCO and DGO and also the cost of ENS in the end of time intervals in the studied case for all aforementioned cases are illustrated in Table 2. The FDM is used to select optimal solutions of Pareto in interval [0–1] in order to find the best solution. Then the minimized- maximized method is implemented to the profits of DISCO and DGO in terms of per-unit (see Fig. 5).

According to Table 2, the best solution for profit of DISCO, DGO and the penalty cost of ENS in case 1 are 6620$, 484$ and 3128$, respectively. As shown in Table 2, the closest solution for DISCO profit and DGO is solution number 13. In this case, DGO has the best profits because, DISCO just relay on rescheduling of DG-ES units. In other words, DISCO does not use reconfiguration or DRP to reduce side effects of probabilistic events, so, DGO resources will cause most of improvement in resilience and DGO owners earn a considerable share of profits caused by REP.

The maximum of DISCO profit equals with 6762$ which is achieved

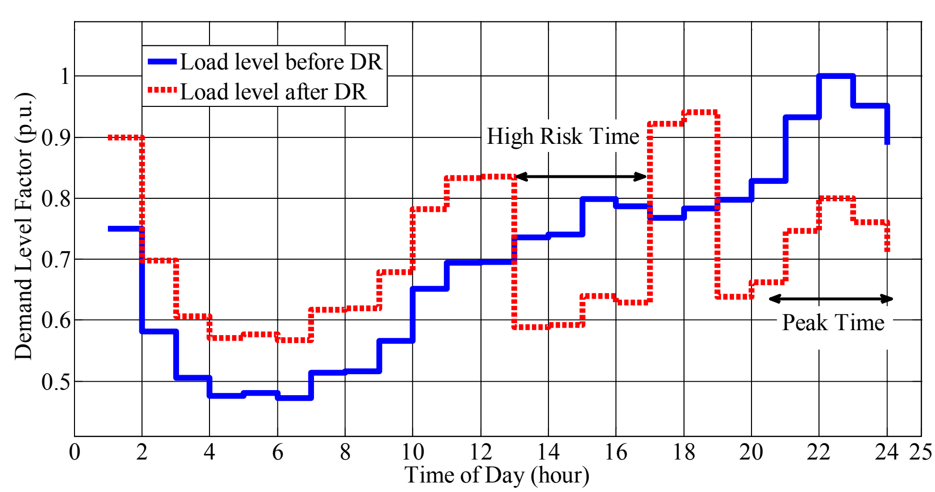

Fig. 6. Impact of proposed operational planning (Case 4) on load profile.

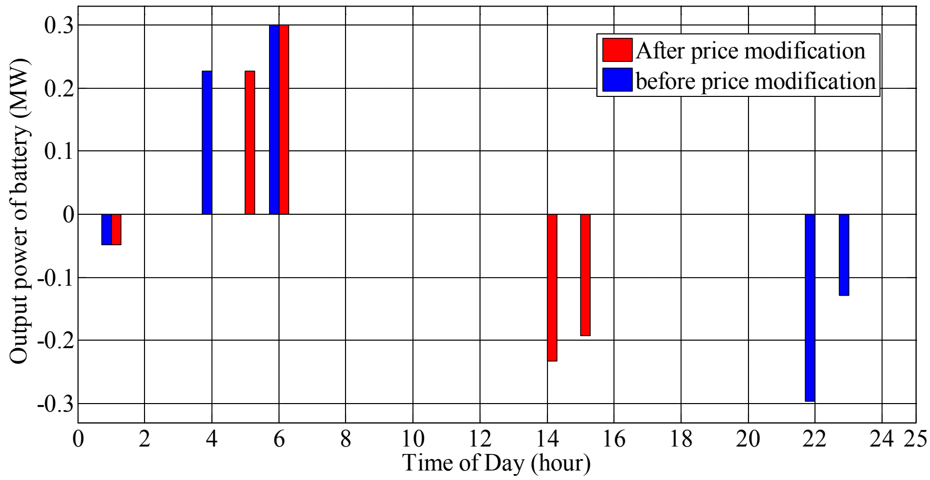

Fig. 7. Impact of proposed operational planning (Case 4) on ES charge/discharge.

from solution number 1. The maximum profit of DGO reaches to 581$ from solution number 20. The profit of DISCO, the profit of DGO and the cost of ENS for case 2 are 7014$, 466$, and 2879$, respectively. The results demonstrate that the best solution is number 12. Also, the results show that dynamic reconfiguration decreases ENS till 8 precent which results to increase of DISCO profit to 6 precent. Additionally, the profit of DGO in this case decreased 3.7 precent. As shown in equation (4), the cost of ENS changes the net cost of energy. The price signal that private section receives is a function of ENS as mentioned in equation (4). So, the price of energy changes with decrease of the value of ENS and consequently the profit of private section decreases. In this case, DISCO uses reconfiguration for minimizing ENS penalty cost and power loss. So, a considerable part of REP benefits are relayed on DISCO actions. In other words, penalty cost of ENS will be less in compared with case 1 and DISCO will earn more profits because of its share on REP. It is noticeable to mention that reconfiguration will reduce average time of outages due to its ability on isolating some damaged lines.

It is worthy to say that the cost of ENS in all-weather conditions is a positive quantity; hence the cost of modified energy (in Equation (4)) always is more that basic price for DGO. In other word the DGO obtain more profit from price change and are interested to cooperate with DISCO. According to Table 2, the operation of REP increases network profit, and consequently this action decreases the penalty cost of ENS. In case 3, the DISCO, the DGO profit and the cost of ENS are 7352$, 451$ and 2494$, respectively. In this case, the profit of DISCO is more than case 1, but the profit of DGO and ENS are 6.8 precent and 20.2 precent is lower than their quantities in case 1, that resulted from REP. In addition, it is obvious that the decrease of ENS has positive effect on DISCO profit and also has negative effect on the DGO profit. The comparison of obtained results of cases 2 and 3 shows that the studied network which uses load shifting is more effective than network reconfiguration. Also, in this case profit of DISCO increased due to its actions for REP improvement.

Case 4 shows results for proposed method, according to Table 2, number 13 solution is the best solution that obtained by considering demand response and reconfiguration in different weather condition. In this case, the profit of DISCO, the profit of DGO and the penalty cost of ENS are 7612 $, 376$ and 1971$, respectively. Increase of DISCO profit and decrease of ENS cost are 15 precent, and 37 precent, respectively. The DGO is faced with 22.3 precent decrease of profit in compare with case 1. In this case, DISCO has the maximum effect on resilience improvement, so, it takes most of profits earned by reducing ENS penalty cost and average outages time. In the proposed method, the effect of REP on consumption curve is shown in Fig. 6. According to this figure, the proposed method, shifts loads from time with high possibility of outage (hour 1 to 5 in afternoon) to other times. Also, proposed method increases DISCO profit and decreases outages volume and ENS cost during extreme weather condition.

In Fig. 7 the injected power from ES is shown for both state of traditional planning and the proposed planning. The positive and negative quantities are related to charge and discharge, respectively.

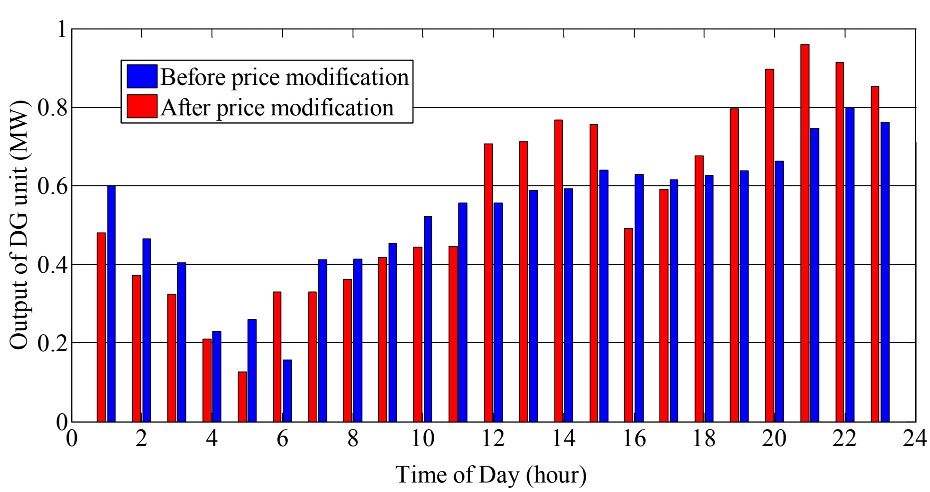

Fig. 8. Effects of proposed method on output of distributed generator (case 4).

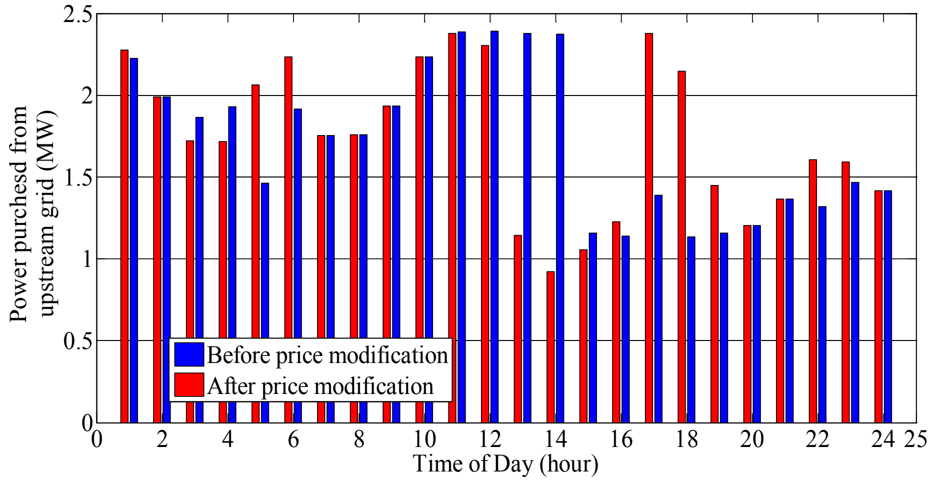

Fig. 9. Effects of proposed method on purchased power from upper networks (case 4).

Table 3
Hourly changes of reconfiguration in the proposed method.

Time (hour)	Open switches	Time (hour)	Open switches
1	6-8-24-31-33	13	6-8-26-30-33
2	6-8-24-31-33	14	6-8-26-30-33
3	6-26-31-33-34	15	6-8-24-31-33
4	6-26-31-33-34	16	6-8-24-31-33
5	6-26-31-33-34	17	6-8-24-31-33
6	6-26-31-33-34	18	6-20-26-31-33
7	6-26-31-33-34	19	6-8-26-30-33
8	6-8-26-30-33	20	6-8-26-30-33
9	6-8-26-30-33	21	6-8-26-30-33
10	6-20-26-31-33	22	6-20-26-31-33
11	6-20-26-31-33	23	6-8-26-30-33
12	6-8-26-30-33	24	6-20-26-31-33

Regarding this figure, in traditional planning, based on lower prices in early hours of morning, the energy storage stays in charge state as much as possible and in peak time, power is injected to grid. In the proposed method, the price of energy is influenced by the cost of ENS. So, power is injected during high risk times when total operational cost for DISCO (ρ_h in Equation (4)) is higher.

Outages rate and the quantity of ENS depend on wind speed. So, during extreme weather condition, the modified price of energy for private section will be increases. In this time intervals the ES unit is set in discharged state. The profit of DGO in these conditions in comparison to case 1 increased due to the growth of energy price. On the other hand, load shifting during high risk hours increase the profit of DISCO, because the required energy decreased during critical condition. In these conditions, energy price due to existing high-risk condition will change.

In Fig. 8, the DG outputs are shown. In traditional planning, power during non-peak hours is provided from upstream grid. Whoever, in the suggested method for operation planning during high risk hours, DISCO increases prices to DGO in order to encourage them to increase output and decrease received power of upper networks. Regarding these modified prices is higher in compare with the prices of traditional operation; the output of DG will be increased to selling electricity. This is shown in Fig. 8, during peak times and the times with high outage risk, the output power of DG is increased in compare with the traditional

Table 4
ΦΛΕΠ metrics for operational and infrastructure resilience.

Case 4	Case 3	Case 2	Case 1	Type	Index
−0.596	−0.714	−0.797	−1	Oper.	Φ
−0.761	−0.761	−1	−1	Infra.	
1.757	1.401	1.255	1	Oper.	Λ
1.316	1.316	1	1	Infra.	
0.393	0.393	1	1	Oper.	E
0.393	0.393	1	1	Infra.	
4.474	3.565	1.255	1	Oper.	Π
3.439	3.439	1	1	Infra.	

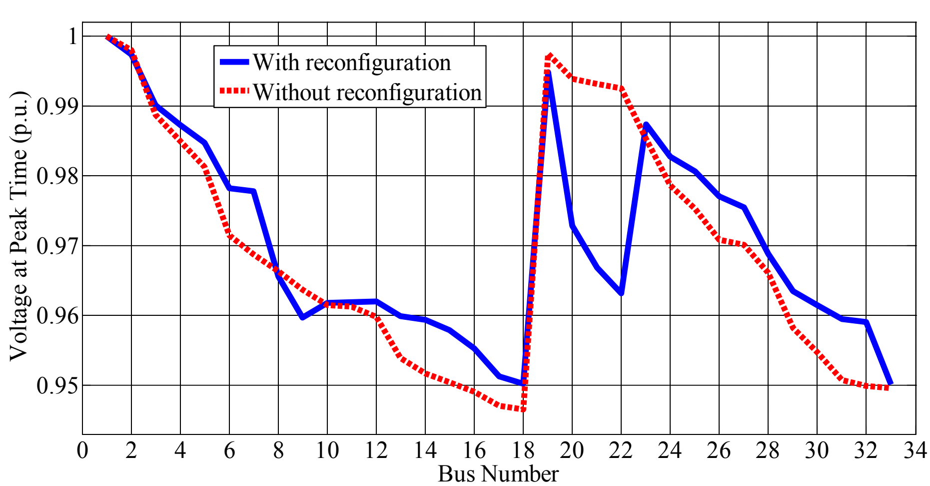

Fig. 10. Effects of proposed method on voltage curve (case 4).

operation.

Fig. 9 demonstrates that the proposed planning decreases the purchased energy during extreme condition from upstream grid. The distribution network inclines toward using local resources. In Fig. 9, it is shown that proposed method increased power generation inside test system and started to inject stored power ES unit to grid. On other hand power import from upstream grid is postponed to time interval between high risk time and peak time (17:00–19:00). This delay is caused by increasing probability of outages in branches in certain time period due to weather condition. Dynamic reconfiguration had provided the possibility of outages reduction by switching. This tendency decreases outage effects on consumers by selecting robust topologies against extreme weather conditions. It is essential to mention that dynamic reconfiguration progressed regarding weather condition and possibility of lines outage and power flow. The possible topologies and hourly changes in terms of conditions are shown Table 3. The presented topologies are derived from an optimization program based on GA. The best topologies are selected by considering risk of outages which is changed by wind speed during 24-hours and power loss which is affected by power flow. Before rescheduling of resource, the effect of wind speed on outage rate of lines is applied and then by considering variable demand level for each time step, optimal topology (by considering predicted wind speed for each time step) is selected. Topologies are represented in this table are obtained from optimization based on probability of branches failure (by prediction of wind speed) and demand level in each hour. It means that there is a determined reconfiguration to minimize the cost of ENS and power loss for each time interval with considering weather condition, load level and power flow. It should be considered that reconfiguration only does not have economical profit but also it improves the technical feature of network such as reduction in ENS. Also, for some faults located in lines which can removed by switching, total reenergizing time in all conditions. For each time interval a certain topology is used. Voltage profile in pick hours is shown in Fig. 10. As shown in this figure, voltage amplitude is sensitive to topologies due to various power flows.

ΦΛΕΠ metrics to evaluate proposed method in the operational and infrastructure resilience improvement are shown in Table 4. These metrics consists three different phases includes, disturbance phases (Φ and Λ–metrics), post-disturbance phases (E-metric) and restorative phases (Π -metric). As results show, in case 2 in compare with case 1, REP improved Φ, Λ and Π operational metrics by 20.3%, 25.50% and 25.50% respectively. In case 2, it is not possible to change topologies so, outage rate of in-service branches not affected by REP. In sequence, Φ, ΛΕΠ metrics for infrastructure resilience not improved in compare with case1.

Also, as there is not any corrective action in case 2 (isolating fault with reconfiguration), so, *E* metric not changed for this case.

In case 3, all ΦΛΕΠ metrics in both operational and infrastructure are improved in compare with cases 1 and 2. It is assumed that fault could be isolated during one hour by reconfiguration, so, post disturbance degraded time for some faults will reduced from 4 h to 1 h and it improve *E* metric by 61.70%. Also, Π metric improved by 256.5% in operational resilience. Infrastructure Φ, Λ, *E* and Π metrics improved by 33.9%, 31.6%, 61.7% and 243.9%, respectively. It is noticeable if fault incepts on certain branches (in main feeder) it is not possible to isolate fault. Comparison between case 2 and case 3 shows that for assumed condition, reconfiguration is more effective than load shifting. Results proved that proposed method for REP has best results in improvement of resilience. As shown in Table IV, Φ, Λ, *E* and Π operational metrics improved 40.4%, 75.7%, 61.7% and 247.4%, receptively. Also, infrastructureΦ, Λ, *E* and Π metrics improved by 33.9%, 31.6%, 61.7% and 243.9%, respectively. In other words, infrastructure metrics in cases 3 and 4 are same due to these metrics are affected by reconfiguration. Also, it is clear that proposed REP using both rescheduling and reconfiguration has best results in compare with others.

As discussed at the beginning of simulation results, for each case the similar weather conditions are considered. In other words, the impact of high-speed wind on probability of lines failure is just considered to illustrate the effect of the proposed method on resilience. However, to validate the obtained results and the proper performance of the proposed model, three wind speeds with different density for each aforementioned case are considered in this section; normal weather condition, high speed winds and extreme weather condition. These wind levels have various averages and probability distributions. It is necessary to mention that normal weather condition means that wind does not change line failure probability. For each simulation time interval, the mean average of wind speed and wind fragility curves are used for calculating outage probability of lines. In this regard, Frequency, duration and number of customer disconnection are employed to evaluate the efficiency of proposed method. The repair time during normal weather condition, high wind speed condition and extreme weather condition are considered 4 h, 5 h and 6 h respectively. Various repair time reflects the difficulty increment of repair crew to fix damaged parts as weather conditions becomes more adverse.

In order to evaluate the impact of proposed method on the resilience indices, different cases are simulated and the key resilience measures showed in Table 5. These case studies are discussed to evaluate the importance of resilient operational planning and reconfiguration.

Table 5 presents number of outages, duration of interruptions and ENS penalty cost for each case study considering different wind speed levels. When wind levels impact is taken into account on the failure probability lines, it is obvious that the resilience indices decrease as lines failure probability increases. In addition, grid resilience indices increase significantly in the extreme wind scenario for proposed method (case 4) due to dynamic reconfiguration and re-scheduling of resource by taking into account the weather condition. In contrast, cases 2 and 4 are less sensitive to the change in the wind speed, as a smaller increase in number and duration of outages is observed with the increase in the wind level. It is clear that reconfiguration makes these cases more resilient to weather-related outages. In other side, rescheduling of resource and demand response programs reduce amount of load during high risk time intervals.

Comparing different cases shows that number of outages and duration of interruptions in cases 2 and 4are lower than cases 1 and 3 for all the wind levels due to selecting robust topologies during higher wind speeds. In other side, the higher resistance and resourcefulness respectively result in lower frequency and duration of power interruptions.

Table 5
Resilience indices for number of outages, interruption duration and ENS penalty cost.

Case studies	**Resilience indices**		
	Number of outages (event/day)		
	Normal	High	Extreme
Case #1	0.065	0.068	0.218
Case #2	0.043	0.047	0.176
Case #3	0.065	0.068	0.218
Case #4	0.043	0.047	0.176
Case studies	**Duration of interruption** (hours/day)		
	Normal	High	Extreme
Case #1	0.067	0.073	0.122
Case #2	0.026	0.028	0.058
Case #3	0.067	0.073	0.122
Case #4	0.026	0.028	0.058
Case studies	**ENS penalty cost** ($/day)		
	Normal	High	Extreme
Case #1	996.52	1175.11	3127.89
Case #2	649.14	707.78	2870.84
Case #3	510.94	583.39	2494.09
Case #4	495.61	542.55	1971.12

Additionally, the number and duration of outages in the cases 1 and 3 are the same in various wind levels which shows reconfiguration has the same impact on duration of interruptions and number of outages. In this case the REP leads to a demand decrement during various wind levels, as a proper reaction to the weather changes. However, number of outages and duration of interruptions in case 2 is less than case 3, but it is clear that REP decreases ENS considerably in all wind levels. Also, regarding wind levels, ratio of ENS in case 3 to case 4 is increased by increment in probability of outages due to wind speed. It is observed in cases 3 and 4 that REP is more effective during higher wind speed. Moreover, it is noticeable that due to the ratio of ENS in cases 2 and 3, it can be found that when wind speed increases, demand response and rescheduling of resources are more effective than reconfiguration. In other words, during higher risk of outages (i.e. higher failure probability), impact of demand response and rescheduling of resources programs are more than reconfiguration.

As concluded from Table 5, developing sufficient situation awareness is critical during extreme weather condition. It is therefore important to coordinate reconfiguration with demand response and rescheduling of resources in various wind levels. Also, it can be found that impact of resources rescheduling, demand response and reconfiguration vary in different wind levels. The simulation results show that proposed method based on REP take advantage of rescheduling, demand response and reconfiguration simultaneously in all wind levels.

5. Conclusion

In this paper, a new method for short-term scheduling of resilience distribution system equipped with DG, ES and automatic switches was investigated. The proposed method is based on changes in weather depended failure probabilities during 24 h time framework, so an adaptive economic- resilient operational planning using dynamic scheduling of resources and reconfiguration considering weather-based outages. In proposed method, it is shown that new grids can consider risk of outages dynamically and change operational planning by considering costs and variation in weather conditions. In order to clarify the weather effect on operational planning, hourly average wind speed is considered and then it modelled on probability of failures on branches. In this paper, resilience enhancement programs increased grid resilience before that any failure inception to minimize side effects of outages by rescheduling of resources and selecting suitable reconfigurations and tried to remove damaged parts by reconfiguration after fault inception. Four different cases with various approaches are considered to study behaviour of a resilience grid during time intervals with high outage probability. Results showed that proposed REP improves resilience and decreases operational costs. Also, for studied test system reconfiguration improved ΦΛΕΠ metrics better in compare with rescheduling. Benefit functions of DISCO and DGO are optimized simultaneously in a multi-objective optimization framework. In all cases weather conditions and outage rates for all time intervals were similar. However, different approaches proved that sometimes economic operational planning during high risk times is different with traditional viewpoint of economic operational planning. The numerical analysis showed that DISCO had the ability to modify energy price for DGO in order to change behaviour of DGO and flexible loads by using higher modified prices. The effectiveness of the proposed method is demonstrated through several case studies.

CRediT authorship contribution statement

Rahman Ashrafi: Software, Formal analysis, Writing - original draft, Data curation. **Meysam Amirahmadi:** Conceptualization, Methodology, Software, Investigation, Writing - review & editing, Project administration. **Mohammad Tolou-Askari:** Validation, Formal analysis, Writing - review & editing, Supervision. **Vahid Ghods:** Visualization, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijepes.2021.106824.

References

[1] Ma S, Su L, Wang Z, Qiu F, Guo G. Resilience Enhancement of Distribution Grids Against Extreme Weather Events. Power Syst IEEE Trans 2018;33(5):4842–53.
[2] Li Z, Shahidehpour M, Aminifar F, Alabdulwahab A, Al-Turki Y. Networked Microgrids for Enhancing the Power System Resilience. Proc IEEE 2017;105(7):1289–310.
[3] Ge Shaoyun, Li Jifeng, Liu Hong, Cao Yuchen, Yang Zan, Yan Jun. Assessing and Boosting the Resilience of a Distribution System under Extreme Weather. Power & Energy Society General Meeting (PESGM) 2019 IEEE; 2019. p. 1-5.
[4] Jia Y, Xu Z, Lai LL, Wong KP. Risk-Based Power System Security Analysis Considering Cascading Outages. IEEE Transon Ind Inform 2016;12(2):872–82.
[5] Wang J, Qin J, Zhong H, Rajagopal R, Xia Q, Kang C. Reliability Value of Distributed Solar+Storage Systems Amidst Rare Weather Events. Smart Grid IEEE Trans 2019;10(4):4476–86.
[6] Mohamed MA, Chen Tao, Wencong Su, Jin Tao. Proactive Resilience of Power Systems Against Natural Disasters: A Literature Review. Access IEEE 2019;7:163778–95.
[7] Hadachi I, Albayrak S. A Survey on Simulation of Power Systems Resilience Under Extreme Weather Events. PowerTech 2019 IEEE Milan 2019:1–6.
[8] Amirioun Mohammad Hassan, Aminifar Farrokh, Shahidehpour Mohammad. Resilience-Promoting Proactive Scheduling Against Hurricanes in Multiple Energy Carrier Microgrids. Power Syst IEEE Trans 2019;34(3):2160–8.
[9] Shanshan Ma, Nichelle'Le Carrington, Anmar Arif, Zhaoyu Wang, Resilience Assessment of Self-healing Distribution Systems Under Extreme Weather Events. Power & Energy Society General Meeting (PESGM) 2019 IEEE; 2019. p. 1-5.
[10] Arif A, Ma S, Wang Z, Wang J, Ryan SM, Chen C. Optimizing Service Restoration in Distribution Systems With Uncertain Repair Time and Demand. Power Syst IEEE Trans 2018;33(6):6828–38.
[11] Ma S, Li S, Wang Z, Qiu F. Resilience-Oriented Design of Distribution Systems. Power Syst IEEE Trans 2019;34(4):2880–91.
[12] Dehghani Nariman L, Darestani Yousef Mohammadi, Shafieezadeh Abdollah. Optimal Life-Cycle Resilience Enhancement of Aging Power Distribution Systems: A MINLP-Based Preventive Maintenance Planning. Access IEEE 2020;8:22324–34.
[13] Sedighizadeh M, Shaghaghi-shahr G, Esmaili M, Aghamohammadi Mohammad Reza. Optimal distribution feeder reconfiguration and generation scheduling for microgrid day-ahead operation in the presence of electric vehicles considering uncertainties. J Storage Mater 2019;21:58.
[14] Omogoye OS, Folly KA, Awodele KO. Review of Sequential Steps to Realize Power System Resilience. SAUPEC/RobMech/PRASA Conference 2020:1–6.
[15] Ding T, Li C, Chen C, Chen B, Yang Y. Risk assessment-based long-term transmission system hardening under prior probabilistic information. Generat Trans Distribut IET 2019;13(1):108–15.
[16] Wang Y, Liu C, Shahidehpour M, Guo C. Critical Components for Maintenance Outage Scheduling Considering Weather Conditions and Common Mode Outages in Reconfigurable Distribution Systems. Smart Grid IEEE Trans 2016;7(6):2807–16.
[17] Matthews LR, Gounaris CE, Kevrekidis IG. Designing Networks with Resilience to Edge Failures Using Two-Stage Robust Optimization. Eur J Oper Res 2019.
[18] Bhusal N, Abdelmalak M, Kamruzzaman MD, Benidris M. Power System Resilience: Current Practices Challenges and Future Directions. Access IEEE 2020;8:18064–86.
[19] Jabr Rabih A, Džafić Izudin, Huseinagić Indira. Real Time Optimal Reconfiguration of Multiphase Active Distribution Networks. Smart Grid IEEE Trans 2018;9:6829–39.
[20] Zhai HF, Yang M, Chen B, Kang N. Dynamic reconfiguration of three-phase unbalanced distribution networks. Int J Electr Power Energy Syst 2018;99:1.
[21] Che L, Zhang X, Shahidehpour M, Alabdulwahab A, Al-Turki Y. Optimal Planning of Loop-Based Microgrid Topology. IEEE Transon Smart Grid 2017;8(4):1771–81.
[22] Lin Y, Bie Z. Tri-level optimal hardening plan for a resilient distribution system considering reconfiguration and DG islanding. Appl Energy 2017.
[23] Arif A, Wang Z, Wang J, Chen C. Power Distribution System Outage Management with Co-Optimization of Repairs, Reconfiguration, and DG Dispatch. IEEE Trans Smart Grid 2017;PP(99):1.
[24] Lei S, Hou Y, Qiu F, Yan J. Identification of Critical Switches for Integrating Renewable Distributed Generation by Dynamic Network Reconfiguration. Sustain Energy IEEE Trans 2018;9(1):420–32.
[25] Liu J, Yixin Yu, Qin C. Unified two-stage reconfiguration method for resilience enhancement of distribution systems. Gen Trans Dis IET 2019;13:1734–45.
[26] Sedzro KSA, Lamadrid AJ, Zuluaga LF. Allocation of Resources Using a Microgrid Formation Approach for Resilient Electric Grids. Power Syst IEEE Trans 2018;33(3):2633–43.
[27] He C, Dai C, Lei Wu, Liu T. Robust Network Hardening Strategy for Enhancing Resilience of Integrated Electricity and Natural Gas Distribution Systems Against Natural Disasters. Pow Sys IEEE Trans 2018;33:5787–98.

[28] Wu X, Wang Z, Ding T, Wang X, Li Z, Li F. Microgrid planning considering the resilience against contingencies. Generat Trans Distribut IET 2019;13(16): 3534–48.
[29] Fang Y, Sansavini G. Optimizing power system investments and resilience against attacks. Reliab Eng Syst Saf 2017;159:161–73.
[30] Farzin H, Fotuhi-Firuzabad M, Moeini-Aghtaie M. Enhancing power system resilience through hierarchical outage management in multi-microgrids. IEEE Trans Smart Grid 2016;7(6):2869–79.
[31] Panteli M, Trakas DN, Mancarella P, Hatziargyriou ND. Boosting the power grid resilience to extreme weather events using defensive islanding. IEEE Trans Smart Grid 2016;7(6):2913–22.
[32] Kianmehr E, Nikkhah S, Vahidinasab V, Giaouris D, Taylor PC. A resilience-based architecture for joint distributed energy resources allocation and hourly network reconfiguration. IEEE Trans Ind Inf 2019;15(10):5444–55.
[33] Panteli M, Mancarella P, Trakas D, Kyriakides E, Hatziargyriou N. Metrics and quantification of operational and infrastructure resilience in power systems. IEEE Trans Power Syst 2017;PP(99):1–10.
[34] Li W, Xiong X, Zhou J. Incorporating fuzzy weather-related outages in transmission system reliability assessment. IET Gen Trans Distr 2009;3(1):26–37.
[35] Caswell HC, Forte V, Fraser J, Pahwa A, Short, Thatcher T, Werner M. Weather normalization of reliability indices. IEEE Trans Power Del 2011;26(2):1273–9.