Resiliency Oriented Operational Planning for Smart Grids under Windstorms

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Weather based power curtailments have a huge share in total customers outage. Hence, reliable-affordable exploitation of networks during the adverse weather condition is one grid operator's main issue. This article addresses an approach for optimal operational by considering dynamic line outages rate during extreme weather condition. In this paper, resiliency modification is accomplished by probing influences of weather condition on line outages using embedded sources, power storages and feeder topology reconfiguration. This work addresses objectives associated with resiliency issue in order to minimize total operation cost from distribution Company's viewpoint, reduce amount of outages and maximize private sector's benefits by probing weather changes during operational time interval. In this regard, a multi-objective optimization problem including both economic and resiliency targets is proposed to model the behavior of distribution company and private sector. Also, a benefit sharing mechanism is applied to increase synergistic integration between these players. A hybrid genetic- constraint strategy employing fuzzy decision maker is applied to achieve optimum Pareto-front solution based on fair profit sharing. Results proves that the proposed method increase profits for all players due to reduction in energy not supplied penalty cost as well as it enhance resiliency during adverse weather conditions.

keywords: *Resilient operation, Profit sharing, Resource rescheduling, Pareto-front solution, Adverse weather condition.*

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NOMENCLATURE

i, j	Bus indices
s	Scenario indices
w	Weather condition indices
L	Load management indices
N_s	Number of scenarios
N_w	Number of atmospheric condition modes
N_L	Number of load management modes
L	Number of thunderbolts
W	Wind speed (m/s)
L_b	Line length (km)
$P^D_{i,dl}$	ith node active power and active load demand before applying DRP (kW)
$Q^D_{i,dl}$	ith node reactive power and active load demand before applying DRP (kVAR)
$S^D_{i,dl}$	ith node apparent power (kVA)
ρ_{dl}	Rate of purchased electricity from up-stream network ($/MW)
λ_{peak}	Peak electricity consumption rate
PLF_{dl}	Price level factor at dl
DLF_{dl}	Demand level factor at dl
N_b	Branch number
N_{wind}	Faults rate due to wind speed (fault/km)
$P^{DRP}_{i,dl}$	Active load demand after applying DRP (kW)
$SD_{P,i,dl,s}$	Shifted active power given by DRP (kW)
$SD_{Q,i,dl,s}$	Shifted reactive power given by DRP (kVAR)
DRP_{dl}	Amount of load contribution in DRP (kW)
λ^P_{sell}	Selling rate of electricity to consumer ($/MW)
λ^{WTG}_{sell}	Purchase rate of electricity from wind unit ($/MW)
$\lambda^{PDGO}_{sell,dl}$	Purchase rate of active power from DG owner ($/MW)
$\lambda^{QDGO}_{sell,dl}$	Purchase rate of reactive power from DG owner ($/MW)
$P^{ch}_{k,dl,s}$, $P^D_{i,dl,s}$	Selling active power to ESS unit and consumer ($/MW)

$P_{k,dl,s}^{dis,in}$	Injected power by batteries (kW)
$P_{dl,s}^{up,pu}$	Purchased active power from main network (kW)
$Q_{dl,s}^{up,pu}$	Purchased reactive power from main network (kVAR)
$P_{j,dl,s}^{WTG,pu}$	Purchased active power from wind unit's owner (kW)
$P_{j,dl}^{DG,in}$	Injected active power from DG unit (kW)
$Q_{j,dl}^{DG,in}$	Injected reactive power from DG unit (kVAR)
$EX_{switching,s,i,dl}$	Reconfiguration expenditure
$EX_{R,dl,s}$	ENS expenditure
EX_{repair}	Repair expenditure ($)
ξ_k^{dep}	Battery depreciation coefficient ($)
η_k^{dis}	Battery discharging efficiency
η_k^{ch}	Battery charging efficiency
A_j, B_j, C_j	Expenditure coefficients for DG production
$\sigma_{i,dl,s}$	Voltage angle
$V_{i,dl,s}$	Node voltage amplitude (Volt)
μ_{rate}	Rate of branch failure (fault/ km)
$\beta_{k,dl}^{ch}, \beta_{k,dl}^{dis}$	Battery charging/discharging binary variables

1. INTRODUCTION

Growth in information technology along with other advanced technologies enhances capability of conventional grids every day. Daily proliferation of embedded systems, storages, electrical vehicle and responsive loads are inevitable. Reliability, economic and security of these grids entails using available tools in an intelligent and smart way [1]. The principal goal of intelligent grid is to optimize grid performance and reliability-resiliency as well as improve technical conditions. Operational planning optimization problems can be classified in two groups. The first group consists of planning during normal conditions and it improves economic-technical based objectives. The second group consists of planning during emergency conditions and it improves stability and load supplement. Various methodologies have been addressed to amplify performance and flexibility of networks based on optimum programming (in normal or emergency situations) of measures, loads, generators, and ES devices [2]. These strategies are based on innovative tools and intelligent exploitations, employ to change the main demand curve and minimize operating costs. Many of these procedures also take the uncertainty of renewable sources, electricity demand, prices, etc. into consideration [3]. Different methods are used for managing uncertainty in decision making algorithms, whose choice depends on the goals and methods of modeling parameters and uncertainty [4]. In many studies, improvements in reliability have been investigated. Power failure statistical data is utilized for most of issues in assessing reliability. However, pointed out strategies does not satisfy operators in terms of adequacy and performance which can be due to the complexity and nonlinearity nature of operating conditions [5]. In [6] for evaluating successive faults to overcome the complexity of computations in emergency analysis, a new method has been introduced, which is based on rescheduling generation using Monte Carlo simulations.

The issue of feeder reconfiguration (FR) has always been considered in electrical energy systems for facing various utilization conditions. The goals of FR and the used methods for solving the problem have been the subject of much research [7–9]. The goals include minimizing losses, improving power quality and load balancing. These used methods are very diverse and include experimental and innovative as well as analytical methods. In [7], the issue of FR and its effect on the power quality, which is related to utilization, has been considered, while in [8] the graph method and programming integers and graph analysis have been considered for optimal planning of micro grids consisting of DGs and storage devices to improve the power quality and solve self-healing problem. In another study [9] using FR, outage management and system repair time optimization has been studied in which DGs have also been used.

In [10] the problem of key placement is solved by minimizing the cost of customers' outage and the cost of installing the keys using integer programming. In this paper, long-term profit and loss analysis is considered for the optimal utilization of a distribution grid by the use of FR. The feature of this review was the uncertainty considered for the load and improving the system capability by reducing the number of customers' outage from the grid. In recent years, flexible loads and generators with renewable energy, especially EVs with the ability to connect to the grid and wind turbines (WTs), have been considered. In [[11], the work with this technology and solving the problem of FR has been studied in their presence. WT output and EVs energy consumption are both considered possible processes and are investigated. Increasing reliability and optimizing utilization costs by hourly FR has been the goal of modeling and solving this problem. This procedure has also been adopted in [12] by taking renewable energy sources into consideration. The difference is that the mathematical model has been considered to reduce losses using hourly FR, in which the mixed quadratic conic programming method has been used, taking into account load changes and the generation of energy sources. In another study [13], optimization of construction investment and utilization has been considered simultaneously. In this research, the DG and load growth is characterized in planning and reconfiguration step. For illustration of feeder topology importance, FR strategy as an old topic is highlighted in planning stage. Ostensibly this category will continue to maintain its importance and evolve with the gradual upgrade of conventional grids towards grids that are utilized more intelligently. If real-time performance is a feature of smart grids, real-time automatic reconfiguration will be an important part of smart grid self-healing operations. In the process of self-healing of the grids, identifying the location of the fault, isolating it from the grid with the minimum customers' outage and meeting their needs from alternative methods automatically or with minimal intervention of human resources is very important. In this way, the resilience of the system increases and the side effects of possible faults are minimized. In the early stages, reliability indicators can be employed to self-healing and resiliency reinforcement procedure. In [14], diverse facets of a grid with self-healing properties in the framework of a multi-factorial system are investigated. Fault isolation, locating, FR, and restoring the system to normal are some of the activities studied in this study. After the fault inception, the grid corrects itself, detects the fault, and after the initial steps, the fault is separated by the action of the appropriate keys. Then, different recovery strategies, according to the existing or defined goals and constraints, follow the sequence of reconfiguration activities in such a way that in the minimum time and minimum output loads, it is possible to redirect power to grid loads. In [15], the mentioned trend in a distribution grid is evaluated. In [16], besides network topology layout, DG planning has been addressed as a multi-objective issue to optimize ENS. summing up studied papers, the studies can be categorized as in the following.

• Papers that demonstrate the importance of economical indexes for both utility and private sector and profit share between them in order to encourage them for investment.

• Papers which conduct a trade-off between at least two opposite targets, such as resilience improvement and economic operation.

• There is lack of attention to resilience improvement while that is ostensibly a challenging obstacle to make smart grid smarter.

The goal of current study is to investigate the behavior of grids in unexpected conditions. This paper shows how a grid can be intelligently utilized to make power outages that are caused by predictable events more resilient with takes into account the impact of different parameters. Unexpected conditions can be storms or thunderbolts.

Breakthrough of this article could be compacted as follows:

• Treatment assessment of intelligent networks during adverse weather condition indicates that resilience grid can maintain the most utilization benefits in a reasonable manner, even in unexpected conditions.

• Employs double-objective optimization for resilient grid that is able to counterbalance risk and profits in a sensible way.

• Generation rescheduling, load variation, unexpected conditions, utilization costs, and resiliency indicators are expressed as an optimization problem in such a way that the system utilizing benefits and private sector is maximized and ENS costs of customers are minimized. Unexpected conditions are modelled according to uncertainty of wind speed in exploitation programming and its impacts on branch outages are investigated.

• The purpose of this paper is based on the fact that purely economic utilization in the situation that the grid is not affected by any events, but increase in probability of an event due to unexpected conditions can be slightly changed to improve the system's ability to cope with possible events in the future.

• The proposed method will prove that in short-term daily planning affects grid profits, private sector benefits and reduction of ENS during bad weather conditions. Although bad weather conditions do not mean a definite occurrence of an event in the grid, by removing part of the grid profit, the amount of costs due to blackouts can be reduced when an incident happens.

The organization of this paper is as follows: The scheduling of resources and FR based on weather condition is introduced in part 2. Optimization modeling is presented in part 3. Case study and results are presented in part 4 and conclusion is last part.

2. OPERATIONAL SCHEDULING AND FEEDER RECONFIGURATION BASED ON WEATHER CONDITION

To gain the resiliency of distribution grids in adverse atmospheric conditions, several measures should be taken into consideration in scheduling. Obviously, in the present case, these measures will depend on weather conditions. The key items used in this scheduling could be including DGs, Demand Response (DR) and Energy Storages (ESs). Rescheduling and reconfiguration along with the use of these items will help system resilience during time intervals with high probability of failure. Utilizing a smart grid learning feature with a history of faults and unexpected conditions can also help the process of making a balance between purely economic utilization and sacrificing some of

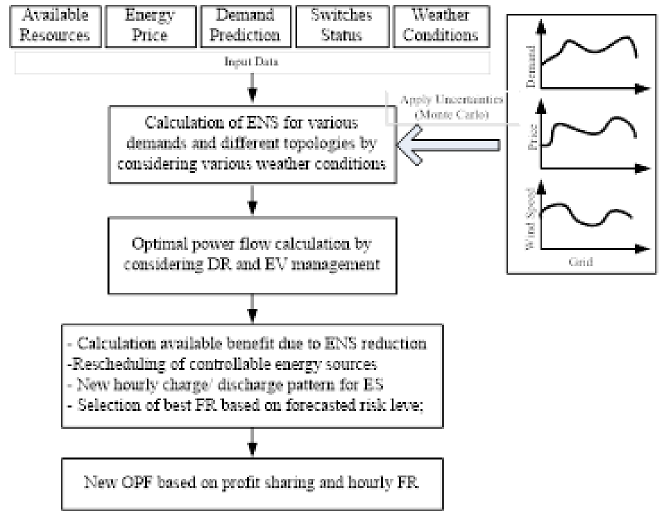

Fig. 1. Schematic of proposed method.

grid profits to reduce side effects outages in extreme weather conditions. It is supposed that during proposed rescheduling, the electricity consumption can be controlled, the necessary FR can be made and the scheduling of the existing resources can be reviewed so that in the worst conditions, the system works optimally and the side effects caused by the event under study become minimal. In the present study, it is shown that flexibility and more intelligent operational planning help the optimal utilization of the grid in extreme weather conditions. Also, it reduces the utilization profit according to changes in weather conditions in the long time framework which will lead to an increased profit of the grid and the private sector. In other words, the probable evaluation of operational planning changes the operational planning methods from one-dimensional economic mode to a hybrid mode including economic variables and resilience indicators. In this case, Demand Response Program (DRP), DG management and FR during unexpected estate guarantees optimal utilization. An overview of proposed process is illustrated in Figure 1. This figure shows the objectives, variables, uncertainties and constraints. In the proposed method, fuzzy decision maker (FDM) and ϵ-constraint strategy are used in GAMS in order to handle double-obj problem. In order to minimize the adverse influence of adverse atmospheric conditions on outages and ENS expenditures, the problem of reconfiguration the grid has been solved in MATLAB software. The outcome of FR is related to the problem of double-objective optimization to approach dynamic FR and rescheduling of resources.

3. MODELING AND PROBLEM FORMULATION

In the proposed optimization model, maximization of private sector benefit and grid operator in exploitation resilient scheduling is the aim of optimization. This optimization is in the context of possible processes due to weather conditions such as uncertainties such as outages caused by wind, energy cost and load. In this study, WT output and weather conditions are independent from the scenarios. Therefore, to obtain different scenarios, the following equation is used:

$$N_s = N_l \times N_w \tag{1}$$

In the above equation, N_s, N_l and N_w are respectively the number of scenarios, the number of modes for load management (two modes with load management and without load management) and the number of modes related to weather conditions on grid costs (taking into account weather conditions and regardless of it).

A. Modeling of load, price, DR and ES

Every day is divided to 24 level, 24 demand level is indicated by Ndl. by multiplying peak load parameter and demand level factor, the model of 24-hour load will be illustrated as in Eq. (2)-Eq. (4):

$$P_{i,dl}^{D} = P_{i,max}^{D_d l} \times DLF_{dl} \tag{2}$$

$$Q_{i,dl}^{D} = Q_{i,max}^{D_d l} \times DLF_{dl} \tag{3}$$

$$S_{i,dl}^{D} = S_{i,max}^{D_d l} \times DLF_{dl} \tag{4}$$

The price of purchased power from upstream grid varies in each level according to amount of electricity consumption and the behavior of power market operator. The price model is described as follows:

$$\rho_{dl} = \lambda_{peak} \times PLFdl \tag{5}$$

The actual price for the grid operator per hour contains the expenditure of purchased power from the main network and possible penalties for outages per hour. Therefore, the actual grid $cost(\rho_{h,s})$ for each hour, which has two definite and probable parameters which can be shown as follows:

$$Cost_{G,s} = \frac{\rho_{dl} \sum_{i=1}^{Nload} + \gamma_l ENS_{dl,s}}{\sum_{i=1}^{Nload}} \tag{6}$$

In the above equation, ρ_P is the amount of fine due to the lack of loads supplement. In this paper, modification in hourly prices is used as a tool in rescheduling to reduce ENS by load transfer to time with lower risk (ENS reduction), DG/ES scheduling and dynamic changes in topologies. In other word, in pervious works DRP used to transfer demand from peak time to off-peak times, but, in this paper DRP is used to transfer demand from high-risk time intervals to other time intervals to reduce ENS penalty cost and overall operation cost of system. There is a similar way for scheduling of resources and reconfiguration. The amount of ENS is obtained as follows:

$$EX_{R,dl,s} = \sum_{b=1}^{N_b} \mu_{rate}.L_b.\rho_p.(\sum_{re=1}^{N_b} P_{res,dl,s} t_{re}) + EX_{repair} \tag{7}$$

In the above equation, N_b is the number of branches in the system, μ_{rate} is the rate of branch failure, L_b is the line length, N_{res}, the number of disconnected busses during outage and repairs, P_{res} is the restored loads after the event happens, t_{res} is the time of fault continuity. Equation Eq. (6) will be used as a signal to implement resilience management programs because these costs include operating costs and blackouts costs. It is necessary to mention that ENS is one of most popular indexes for reliability and resiliency evaluation due to its concept. The value of ENS is affected by characteristics like extent lengthwise of the grid line and outage rate in grid components in each kilometer. In order to reduce its costs, the grid operator implements a DRP to change the consumption behavior of its customers and to shave the consumption peak and fill the valley of load curve. It is worth to be pointed out that in current paper the transferred capacity by consumers is limited. It is estimated that only 15% of the total load is used in the DRP. The DRP can be modeled as Figure 2.

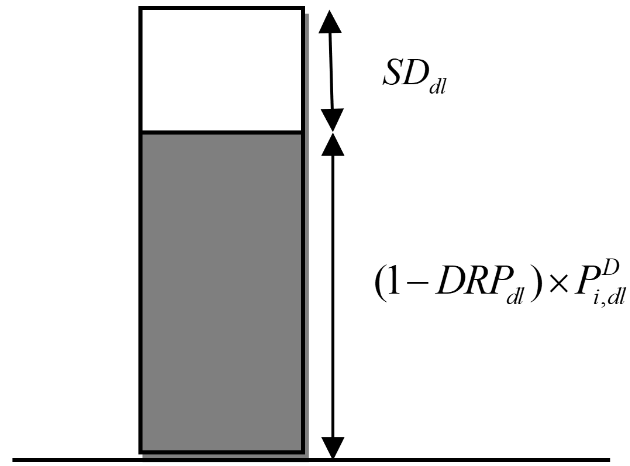

Fig. 2. Load modeling based on DRP.

The dashed line part in Figure 2 is the part of the load that cannot participate in the DRP, while other parts of the load can be moved to different time intervals due to price changes. The mathematical model of Figure 2 is as follows, which shows the load transfer (active power and reactive load simultaneously and with constant power factor). The DRP used is of the time of use type. It is also assumed that the amount of active and reactive power load transfer from all busses is done with a constant percentage and the load transfer from each bus is with a constant power factor for that bus.

$$P_{i,dl,s}^{DRP} = P_{i,dl,s}^{D} + SD_{P,i,dl,s} \tag{8}$$

$$Q_{i,dl,s}^{DRP} = Q_{i,dl,s}^{D} + SD_{Q,i,dl,s} \tag{9}$$

$$SD_{P,i,dl,s} = DRP_{dl,s} \times P_{i,dl,s}^{D} \tag{10}$$

$$SD_{Q,i,dl,s} = DRP_{dl,s} \times Q_{i,dl,s}^{D} \tag{11}$$

$$\sum_{dl=1}^{24} SD_{P,i,dl,s} = \sum_{dl=1}^{24} SD_{Q,i,dl,s} = 0 \tag{12}$$

$$DRP^{min} < DRP_{dl,s} < DRP^{max} \tag{13}$$

Equations Eq. (11) - Eq. (13) shows the relevant constraints on DRP. The changeable demand at each load level has a variable value that is shown by DRP_{dl} and is shown in equation Eq. (13). The DRP_{dl} index indicates consumer participation in DRP. Equation Eq. (13) limits the increase in demand over any time period. In this article, the proposed method is implemented in such a way amount of outages due to unexpected conditions is minimized.. One of the optimization goals is resilience reinforcement. In current article ENS index is addressed to highlight the significance of system uncertainty. If there are distributed energy resources with island operation capability and ES in the distribution system, these power sources are used as a source to feed loads that have been cut off due to faults in transmission lines or distribution systems. And thus, the resilience of the system increases.

B. Objective Function

The performance model is a combination of distributed sources and other ESs. The grid is able to trade power with distributed resource operators as well as upstream-network. Maximizing of daily profit of power trading is the main term of exploitation framework.

Equation Eq. (14) shows the mathematical formula of the grid operator profit.

$$OF_{1,s} = \sum_{t=1}^{N_{dl}} \Bigg\{ \sum_{i=1}^{N_{load}} \lambda^{P}_{sell,dl,s} \cdot P^{D}_{i,ds,l} + \sum_{i=1}^{N_k} \lambda^{P}_{sell,dl,s} \cdot (P^{ch}_{k,ds,l} - P^{dch}_{k,ds,l}) \tag{14}$$
$$- \sum_{up=1}^{N_{up}} \lambda_{dl} \cdot P^{up,pu}_{dl,s} - \sum_{up=1}^{N_{up}} \lambda_{Qfix} \cdot Q^{up,pu}_{dl,s} - \sum_{i=1}^{N_{switch}} (EX_{switching,s,i,dl}$$
$$-EX_{R,dl,s}) - \sum_{j=1}^{N_{WT}} \lambda^{WTG}_{sell,dl} \cdot P^{WTG,pu}_{j,dl,s} - \sum_{j=1}^{N_{DG}} \lambda^{PDGO}_{sell,dl,s} \cdot P^{DG,in}_{j,dl,s}$$
$$- \sum_{j=1}^{N_{DG}} \lambda^{QDGO}_{sell,dl,s} \cdot Q^{DG,in}_{j,dl,s} \Bigg\}$$

The profit of selling electricity to consumers, purchased electricity expenditure from upstream-network or power market, expenditure of purchased reactive power, ENS expenditure, and purchased energy from RESs owners are described as terms of 1th obj-function in equation Eq. (14), respectively. The renewable energy operator's profit comes from the sale of energy to the grid. The renewable energy operator also invests in batteries. The price at which operators sell their renewable energy sources is affected by their role in power market. They can sell their energy under a bilateral contract at market price. The renewable resources are the profit function of the operator and are calculated as Eq. (15).

$$OF_{2,s} = \sum_{t=1}^{N_{dl}} \Bigg\{ \sum_{j=1}^{N_{DG}} \lambda^{PDGO}_{sell,dl,s} \cdot P^{DG,in}_{j,dl,s} + \sum_{j=1}^{N_{DG}} \lambda^{QDGO}_{sell,dl,s} \cdot Q^{DG,in}_{j,dl,s} \tag{15}$$
$$+ \sum_{j=1}^{N_{WT}} \lambda^{WTG}_{sell,dl} \cdot P^{WTG,pu}_{j,dl,s} + \sum_{k=1}^{N_k} \lambda^{P}_{sell,dl,s} \cdot P^{dis,in}_{k,dl,s} - \sum_{k=1}^{N_k} \lambda^{P}_{sell,dl,s} \cdot P^{ch}_{k,dl,s}$$
$$-\zeta^{dep}_{k} \Big(\sum_{k=1}^{N_k} \frac{P^{dis,in}_{k,dl,s}}{\eta^{dis}_{k}} + \eta^{dis}_{k} \cdot P^{ch}_{k,dl,s} \Big) - \sum_{j=1}^{N_{DG}} (A_j P^{2}_{j,dl,s}{}^{DG,in}$$
$$+B_j P^{DG,in}_{j,dl,s} + C_j) = \sum_{j=1}^{N_{DG}} Q^{DG,in}_{j,dl,s} \cdot CT^{Q}_{j} \Bigg\}$$

Benefit gaining from selling electricity to up-stream grid, the benefit of ESS exploitation, the expenditure of battery charging in which case the batteries act as a consumer for the network, the expenditure of battery depreciation and exploitation expenditure of DGs for active power generation are addressed as terms of second obj-function in equation Eq. (15). Respectively. A_j , B_j and C_j are also cost coefficients for producing the distributed generation resources which can be controlled.

Given the effects of resiliency in enhancement of economic-technical factors of grid, it is visible that optimal operational planning leads to considerable benefits for all players. Therefore, giving incentives for private sector to more cooperation is a logical solution to resiliency improvement. In this regard, mentioned multi-objective optimization functions include an index (β) for ENS reduction due to cooperation between owner of grid and private sources. Objective functions are presented in two cases, with β coefficient and without β coefficient:

$$OF1 = OF1_{with_cooperation} - \beta \times (OF1_{with_cooperation} - OF1_{without_cooperation}) \tag{16}$$

$$OF2 = OF2_{with_cooperation} - \beta \times (OF2_{with_cooperation} - OF2_{without_cooperation}) \tag{17}$$

Swing profit (profit gained by grid operator due to private sector instruction) sharing helps private sector to increased flexibility of rescheduling.

C. Constraints

The load distribution constraints and equations shall be at i^{th} bus and the level of dl^{th} as follows. It should be noted that the owners of DG and ESS units are assumed to be common. On the other hand, wind units, unlike thermal units, do not have a variable cost with generation and generally have a fixed cost due to depreciation, which is independent of the amount of generation.

$$P^{up,pu}_{dl,s} + P^{DG,in}_{i,dl} - \big((1-DRP_{dl}) \times P^{D}_{i,dl,s} + SD_{P,dl,s}\big) + \sum_{k=1}^{N_k} (P^{dis,in}_{k,dl,s} - P^{ch}_{k,dl,s}) = V_{i,dl,s} \sum_{j} V_{j,dl,s} (G_{ij} cos\sigma_{i,dl,s} + B_{ij} sin\sigma_{j,dl,s}) \tag{18}$$

$$Q^{up,pu}_{dl,s} + Q^{DG,in}_{i,dl} - \big((1-DRP_{dl}) \times Q^{D}_{i,dl,s} + SD_{Q,dl,s}\big) = V_{i,dl,s} \sum_{j} V_{j,dl,s} (G_{ij} cos\sigma_{i,dl,s} + B_{ij} sin\sigma_{j,dl,s}) \tag{19}$$

The node voltage at any given time must be kept within its permitted range.

$$V^{min}_{i} \le V_{i,dl} \le V^{max}_{i} \tag{20}$$

The active and reactive power produced by each bus is shown as follows:

$$P^{up,pu}_{min} \le P^{up,pu}_{dl,s} \le P^{up,pu}_{max} \tag{21}$$

$$Q^{up,pu}_{min} \le Q^{up,pu}_{dl,s} \le Q^{up,pu}_{max} \tag{22}$$

The generation capacity of each of the distributed generation sources must also be within their permitted range.

$$P^{DG,pu}_{min} \le P^{DG,pu}_{dl,s} \le P^{DG,pu}_{max} \tag{23}$$

$$Q^{DG,pu}_{min} \le Q^{DG,pu}_{dl,s} \le Q^{DG,pu}_{max} \tag{24}$$

At all levels, the transmission power through the lines is limited by their thermal limit.

$$S_{ij,dl} \le S^{max}_{ij} \tag{25}$$

Equations Eq. (26) - Eq. (30) show the constraints related to ESS. Constraints Eq. (26) - Eq. (28) demonstrates the boundary of battery charging/discharging furthermore the amount of stored electrical power in the ESS. Equation Eq. (29) illustrates that the battery ESS can be on only one mode at any time. The dynamic model of ESS is shown in equation Eq. (30).

$$0 \leq P^{ch}_{k,dl,s} \leq \beta^{ch}_{k,dl} P^{ch,max}_{k} \tag{26}$$

$$0 \leq P^{dis}_{k,dl,s} \leq \beta^{dis,in}_{k,dl} P^{dis,in,max}_{k} \tag{27}$$

$$BE^{min}_{k} \leq BE_{k,dl,s} \leq BE^{max}_{k} \tag{28}$$

$$\beta^{ch}_{k,dl,s} + \beta^{dis}_{k,dl,s} = 1 \tag{29}$$

$$BE_{k,dl+1,s} = BE_{k,dl,s} + (\eta^{ch}_{k} \cdot P^{ch}_{k,dl,s} = \frac{P^{dis,in}_{k,dl,s}}{\eta^{dis}_{k}}) \tag{30}$$

D. modeling of outages

The results of various studies indicate that storm is main reason for largest part of the failures in electrical distribution grids [17]. In a smart grid, recording data related to these events can help improve the performance of these grids in the above conditions. However, not all grids have this technology. In this study, outages are studied in two categories. The first part includes faults due to environmental pollution, the role of animals and other faults caused by unknown reasons. The coefficient of this type of events is considered constant. In the second part, faults due to storm are taken into consideration. In order to analyze properly for evaluating the outcome of weather condition on the number of outages, the correlations presented in [18] are used for modeling. To prob the treatment of flexible grids in different weather condition the normal data are applied in simulations due to lack of real data of weather incidents. The value of wind speed is assumed to be foreseeable at one-hour intervals. In [18] the relationship between incidents and wind speed is presented for small distances using the equation Eq. (31):

$$N_{wind} = 0.0012W_s^2 - 0.0131W_s \tag{31}$$

In current article the mean value of wind speed is applied per time interval. Wind speed affects outages number and thus it alters the output of WTs. The uncertainty of wind speed change pattern needs to be estimated for each region. In this study, to evaluate the effect of wind, N_{wind} is assumed to be variable during the day to evaluate the sensitivity of the power grid to this factor. In case of outage in the grid, the time required for repairing depends on the type of outage, its location and weather conditions. Obviously, in storm condition, more time will be needed for repairing [17]. In one study, the repair time was 4 hours in normal conditions, and in extreme conditions, the average was estimated as 6 hours [18]. Therefore, wind speed N_{wind} and the number of lightning strikes N_{Th} will affect the repair time and the amount of ENS.

E. Resilience Evaluation Metrics

In this Paper, in order to evaluate resilience improvement of proposed method, ENS as most popular metric in reliability and resiliency evaluation and also, $\Phi\Lambda E\Pi$ metrics proposed in [19] are calculated. ENS metric can present effect of proposed method in value of outages. Also, based on $\Phi\Lambda E\Pi$ metrics, system can operate in different operational phases as shown in figure 4. In order to prove effectiveness of proposed method

Table 1. Metrics for operational and infrastructure [19].

Metric	Mathematical Formula		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/hr	Lines tripped/hr
Λ	$R_{0o} - R_{pdo}$	$R_{0i} - R_{pdi}$	MW	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/hr	Line restored/hr

(during windstorms) and study effects of resources rescheduling, load management and effective reconfiguration in resilience oriented operational planning, results will be evaluated by mentioned metrics. Different phases of operation in [19] are proposed by resilience trapezoid model. In mentioned model three various states are the disturbance state (Φ and Λ–metrics), post-disturbance state (E -metric) and restorative state (Π -metric). In [19], mathematical formulations for $\Phi\Lambda E\Pi$ metrics are defined for both operational resilience R_{pdo} and infrastructure $\left(R_{pdi}\right)$ resilience.

Mathematical formulas for $\Phi\Lambda E\Pi$ metrics are presented in Table 1 [19].

F. Solution method

The uncertainties and different constraints are increasing complexity of multi-objective problem. In this regard, a multi-objective genetic algorithm approach is used to solve optimization problem. In order to model uncertainties of outages, Monte Carlo method is used. By considering variable β to benefit sharing between grid operator and private sector, a method for β selection is vital. In current article, -constraint technique is applied according to [20] probing optimal profit sharing condition using crowding distance. Also, the FDM uses Pareto optimal solutions to achieve optimum Pareto-front. The FDM assigns a fuzzy membership function to all available Pareto solutions. In this study, the minimum-maximum approach is used for a compromise between the existing optimal solutions. Choosing maximum amount of the least benefit for each obj-function as the optimum outcome is the basic approach of this trial. In order to grid feeder reconfiguration and then the achieved topology is excreted to multi-objective mathematical problem (MOMP), genetic algorithm is used. Wind speed, thunderbolts probability and load level are employed in GA. Changing atmospheric condition at various time intervals of demand whether at consumption peak or other hours lead to various figures for each temporal period. Reducing ENS expenditure is the goal of GA trial with intention to minimize grid exploitation expenditure. After choosing optimum grid topology per temporal interval, optimum programming regarding real-time energy price is modified and applied to the supply units and demand buses to manage the undesired influences of adverse atmospheric condition and to establish a counterbalance between resiliency and economic performance. It should be noted that the incidence of adverse atmospheric condition does not mean the random inception of an event in the grid, but in terms of probability, the outage rate of the lines is highly dependent on atmospheric condition, and therefore as the atmospheric condition get worse, the grid takes measures to improve the capability of dealing with probable conditions. This in turn reduces grid profits in proportion to the severity of the risk due to atmospheric condition, but as it will be demonstrated in the following part, with proper management,

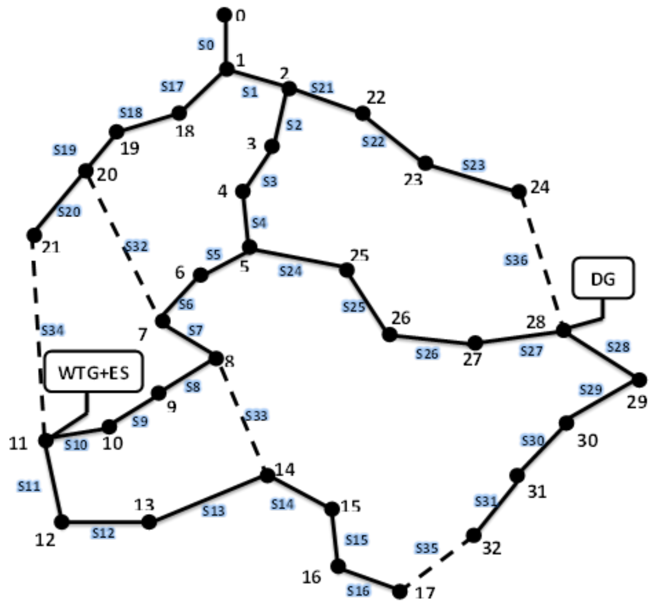

Fig. 3. The studied 33 bus test system.

Table 2. Comparison of optimum Pareto solutions.

Results in case without considering resiliency		DisCo profit ($\$/day$)	Private sector profit ($\$/day$)
Without DRP	Ref. [20]	6022	1704
	Proposed method	6127	1653
With DRP	Ref. [20]	6177	1688
	Proposed method	6284	1611

grid profits will amplify in the long-temporal intervals. In order to improve resiliency, simulations are performed by variable index (β).

4. SIMULATION RESULTS

The proposed approach is used for the standard 33-bus grid, shown in Figure 3. In the understudied grid, 5 sectionalizing switches are probed. The test system information is extracted from the reference [21] with modifications to study the present problem. A DG and a WT with nominal capacity of 1 MW for each one are located in nodes 11 as well as 28. A storage system with 0.6 MW capacity enabling charging/discharging level of 300 kilowatt is located in node 11. The boundary of stored energy in mentioned storage unit is between 100-600 kWh. The temporal duration for exploitation programming is probed to be an hour. In this trial, the ENS expenditure is probed as an indicator of grid resiliency.

In this paper in order to prove validation and accuracy, results of simulations are compared with results obtained from reference [21]. Information is extracted from mentioned reference and used in similar formulations and data. As, there is not any resiliency improvement in [21], so the objective function is reformed to check accuracy. Comparisons of results are shown in Table 2. The results prove that for similar objective functions and data, the results are close to each other. In the next, with intention to prove effectiveness of presented operational planning, the cases mentioned in the following part are probed in which

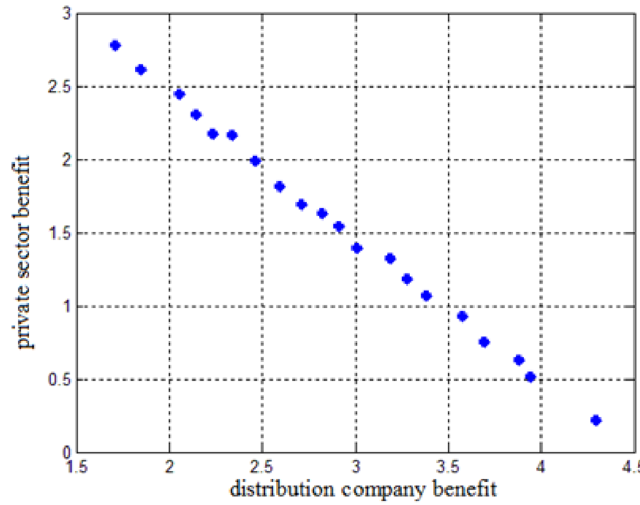

Fig. 4. Pareto solutions ($\beta \neq 0$).

reconfigurations have been made to reduce the ENS in the grid.

1st Case: exploitation programming, DRP and grid feeder reconfiguration are not involved

2nd Case: exploitation programming, considering feeder reconfiguration and DRP is not involved

3rd Case: exploitation programming, considering DRP and feeder reconfiguration is not involved

4th Case: exploitation programming regarding DRP and grid feeder reconfiguration

Adverse weather affects all cases on exploitation programming and ENS expenditures are computed per temporal intervals. Also, outage rate and repair time for all components are the same. The optimum grid topology selection for each wind speed and number of lightning strikes is calculated according to the level of demand and energy prices using a GA and then used to optimize exploitation programming.

It is assumed that grid operator shares a part of benefits earned by resiliency improvement (ENS reduction) with private sector due to rescheduling in private sector resources to ENS reduction. In this regard, a variable β is considered in non-inferior solutions. For positive values of β, related solution is acceptable for both parties, However, the value of benefits for each side is different for various β amounts. The obtained Pareto solutions is shown in Figure 4.

A set of Pareto is obtained for the system for all probed cases. The benefit for the distribution company as well as the private sector furthermore the ENS expenditures at the end of this trial for all of above cases conformed in Table 3. In this Table, amounts of OF_1 and OF_2 and in sequence the best solution (maximizing min (OF_1, OF_2) named by C.D) is shown. In order to attain the optimal Pareto the FDM is applied in the range [0-1] to allocate the desired Pareto. Then, the minimum-maximum procedure is applied to the gained benefits of the distribution company and the private sector.

Changes in β parameter will change profits of all players earned by ENS reduction due to resources re-scheduling. For each value of β parameter, a certain operational planning exists. In simulation results, the effects of DRP on operation cost and gained benefits are studied. It is proved that using DR increase flexibility of grid in order to improve resiliency and as well as it increase economic profits for grid operator. As table 2 confirms, the optimum Pareto for grid profits, private sector and

Table 3. A set of optimum Pareto fronts for the probed cases.

Case #	Pareto Solution	Utility	Private sector	ENS expenditure
1st Case	1	6762.3	317.6	3154.2
	13	6620.2	484.1	3128.7
	20	6306.5	581.1	3119.2
2nd Case	1	7203.8	277.3	2894.8
	12	7013.7	465.5	2878.8
	20	6693.6	575.7	2861.9
3rd Case	1	7523.7	268.1	2530.4
	13	7351.5	451.2	2494.9
	20	7160.1	557.4	2489.7
4th Case	1	7739.3	269.9	1985.1
	13	7612.1	376.1	1970.9
	20	7383.5	446.6	1969.3

ENS expenditures in 1th case are $6620.2, $484.0 and $3128.8, respectively. Regarding to Table 3, the nearest Pareto solution to the benefit of electricity grids and private sector is Pareto Solution 13. The maximum grid profit is equal to $6762.4, which is obtained in the number one solution. The best Pareto solution for private sector is number 20 which is $581.0. Grid profit, private sector owner's benefit and ENS expenditure for case 2 are $7013.8, $465.6 and $2878.9, respectively. The outcomes demonstrate that the desired set of Pareto solution is number 12. The outcomes also confirm that dynamic grid feeder reconfiguration reduces the expenditure of ENS by 7.99%, which in turn increases grid profit by 5.95%.

Private profitability is also reduced by 3.80% in this case. The expenditure of ENS modifies the rate of electricity, as described in Equation Eq. (6). The original and modified prices are presented in Figure 6. It is noticeable that DRP based on resiliency enhancement uses modified prices. In other word, a considerable difference between proposed method and other similar methods is in price modification. The price signal received by the private sector's owner is a function of ENS. Therefore, as the value of ENS decreases, electricity rates change and private sector profits decrease. It is worth noting that the expenditure of ENS is positive in all atmospheric condition, so the rate of modified energy is always higher than the base rate for private sector. In other words, the private sector always makes more profit after the price change and thereby absorbs electricity grid operator to cooperate. As shown in Table 2, demand response operations increase grid profits, which reduce private sector's owner benefits and the expenditure of ENS. In the case of 3, grid profits, private sector profits, and ENS costs are $7351.6, $451.0, and $2494.0, respectively. Thereby, the benefit of network operator is 11% more than the 1th case, in the other side the benefit of the private sector's owner and the expenditure of ENS are 6.81% and 20.29% under their values of 1, which is for the sake of DRP. It is also revealed that alleviating the expenditure of ENS has a positive effect on grid profits as well as a negative impact on the profits of private sector. Collation of the outcomes obtained in cases 2 and 3 confirms that in the studied grid, the use of DRP is more effective than grid reconfiguration.

4th case demonstrates the outcomes of the employed methodology. As is conformed by Table 1 Pareto Solution 13 is the desired Pareto attained by probing load responsiveness and grid dynamic reconfiguration in various atmospheric condition,

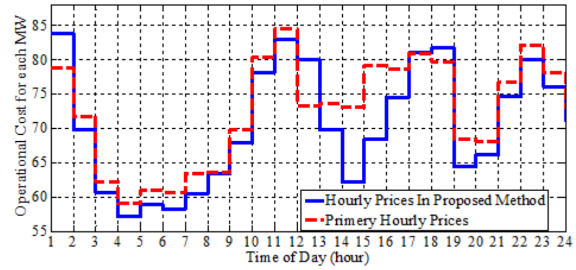

Fig. 5. Changes in hourly prices in proposed method.

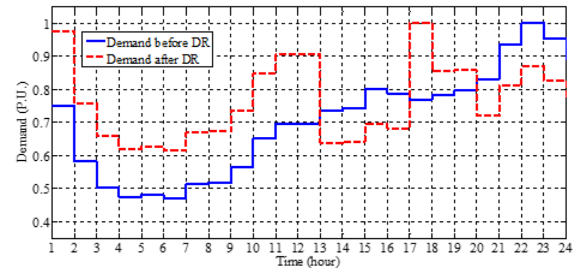

Fig. 6. Effect of employed exploitation programming (4th case) on load curve.

which grid profits, private sector profits, and ENS costs are $7612.1, $376.1, and $1970.9, respectively. The normalized network operator's benefit and private sector's owner benefits used in the Pareto method are shown in Figure 3. Increment of the utility operator's benefit and decrement ENS expenditure are 14.99% and 27.00%, respectively. The private sector is facing a 22.28% decrease in profits in 1st case.

In introduced approach, the efficacy of DRP on the demand curve is conformed by Figure 5. As is obvious, the employed DRP shifts consumption from peak hours to other times, in which case grid profits increase and reducing the expenditure of ENS in adverse weather is guaranteed. Using a DR program will increase energy availability however, weather will also affect the whole range.

Figure 7 shows the power received from the battery for both conventional and optimal programming modes. Charging and discharging process are associated with positive value of curve and negative one, respectively. Considering this figure, in conventional system mode, for the sake of lower electricity rate in the early morning hours, the battery ESS is in charge mode as much as possible and injects power into the distribution grid during peak load. In the current methodology, the electricity rate is under effect of ENS expenditure. There is a correlation between failure rate and ENS value with wind speed and thunderbolts strikes. Therefore, in adverse atmospheric condition, the offered electricity rate to the private sector's owner will increase. During these time periods, the storage unit is discharged. The profits of the private sector are higher in the conventional grid due to rising energy prices. On the other hand, changes in the process of shifting the load from high-risk hours to hours with better weather conditions increase the utility owner's benefit, for the sake of decrement of energy demand in urgent situations. In these circumstances, ENS value changes due to forecasted risky conditions.

The outcome of DG unit conforms by figure 8. In conven-

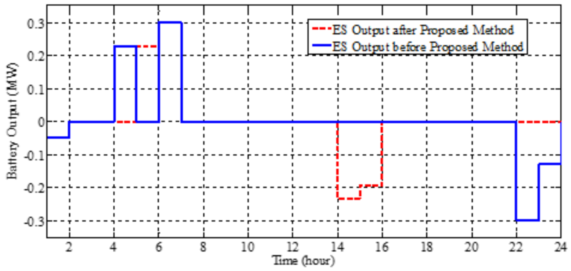

Fig. 7. Effect of employed exploitation programming (4th case) on battery ESS charging/discharging procedure.

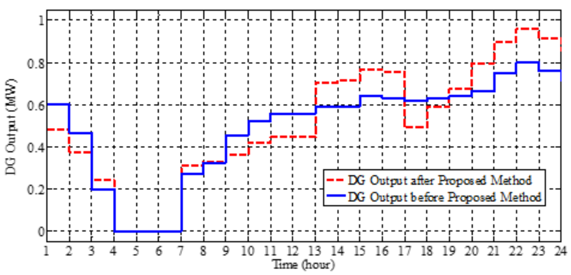

Fig. 8. The effect of the proposed approach on DG.

tional scheduling, the grid provides electricity during off-peak hours from the main network. However, in the current exploitation programming, in high-risk periods, the embedded system operator enhances the rates to interact with the DG to reduce the received power from the upstream grid. Considering that revised prices are higher than conventional operational planning prices, DG will tend to sell electricity.

It is confirmed by Figure 8 that at consumption-peak and high risk hours of power outages, the generation of DG modifies in collation with conventional mode. Figure 9 shows that in proposed planning, energy purchased from the upstream network is reduced in unexpected conditions and the distribution network tends to use local resources. This procedure reduces the effects of outages on ENS. Because dynamic reconfiguration in these conditions also allows the use of local resources.

It should be noted that the dynamic reconfiguration of the network is also running during the mentioned process. Reconfiguration is done according to the atmospheric condition, the necessities of supply unit and the possible risk of branch failure. Attained topologies in exploitation programming and hourly modification are illustrated in Table 4. This means that for each

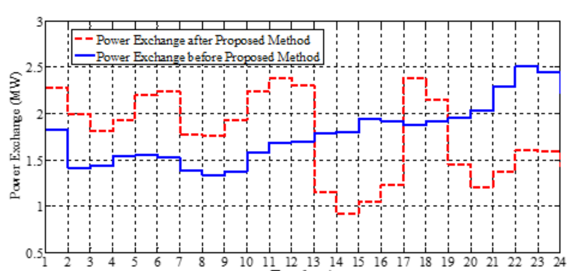

Fig. 9. . The effect of the proposed approach on the purchased electricity from the main network.

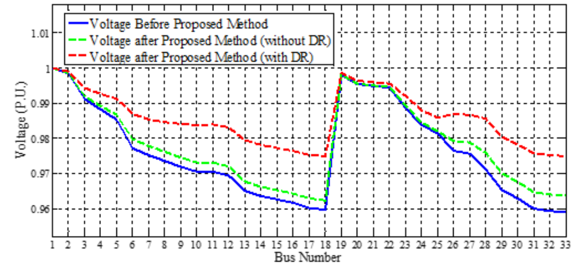

Fig. 10. The effect of proposed approach on voltage profile.

Table 4. Changes in grid topology in proposed method for 24 hours.

Demand Level	Grid Topology	Demand Level	Grid Topology
1	5-7-23-30-32	13	5-7-25-29-32
2	5-7-23-30-32	14	5-7-25-29-32
3	5-25-30-32-33	15	5-7-23-30-32
4	5-25-30-32-33	16	5-7-23-30-32
5	5-25-30-32-33	17	5-7-23-30-32
6	5-25-30-32-33	18	5-7-23-30-32
7	5-7-25-29-32	19	5-7-25-29-32
8	5-7-25-29-32	20	5-7-25-29-32
9	5-7-25-29-32	21	5-7-25-29-32
10	5-19-25-30-32	22	5-19-25-30-32
11	5-19-25-30-32	23	5-19-25-30-32
12	5-19-25-30-32	24	5-19-25-30-32

time period, there is a certain topology for minimizing ENS costs and losing power, which results in minimal changes in energy prices for the grid. On the other hand, it is clear that in any case, these minimal changes will increase the price compared to normal hours. DG and ES will benefit in this situation. It should be noted that reconfiguration improves benefits the economy as well as technical issues, such as voltage as shown in Figure 10.

$\Phi\Lambda E\Pi$ metrics which present effectiveness of resilience oriented operational planning are shown in Table (4). For all operational states (include: disturbance state (Φ and Λ–metrics), post-disturbance state (E-metric), and restorative state (Π - metric)), results prove that proposed method has better outputs. Also, effect of resource re-scheduling, demand response and dynamic reconfiguration are studied based on various cases. In Table 5 results show that in case 2, resilience operational planning improves Φ,Λ and Π metrics up to 20.2%, 25.6% and 25.6% in compared with case 1, respectively. In case 2, reconfiguration is not applied, so, outage rate didn't change, compared with case 1. In similar way, damaged lines isolating using reconfiguration is not possible. So, E metric is not improved.

In case 3, both operational and infrastructure metrics are better, compared with previous cases. Reconfiguration will isolate some faults in certain lines. It is assumed that reconfiguration can isolate certain faults in one hour. In other words, post-disturbance degraded time can be reduced from 4 hours to 1 hour for some faults and it leads to improvement in E metric around 60.6% and Π metric to 244.0%. Also, $\Phi\Lambda E\Pi$ metrics for infrastructure are improved to 23.8%, 31.7%, 60.6% and 244.0%,

Table 5. $\Phi\Lambda E\Pi$ metrics for operational and infrastructure resilience.

Index	Type	Case 1	Case 2	Case 3	Case 4
Φ	Oper.	-1	-0.798	-0.715	-0.597
	Infra.	-1	-1	-0.762	-0.762
Λ	Oper.	1	1.256	1.402	1.758
	Infra.	1	1	1.317	1.317
E	Oper.	1	1	0.394	0.394
	Infra.	1	1	0.394	0.394
Π	Oper.	1	1.256	4.475	4.475
	Infra.	1	1	3.440	3.440

respectively. Results evaluation for case 2 and case 3 show reconfiguration has stronger effect in resiliency improvement in compared with load shifting. Results verify that proposed method for REP has best results in improvement of resilience. As shown in Table 4, in case 4,$\Phi\Lambda E\Pi$ metrics for operational are improved 40.3%, 75.8%, 60.6% and 347.5%, receptively. Also, infrastructure Φ,Λ, E and Π metrics improved by 23.8%, 31.7%, 60.6% and 244.0%, respectively. It is obvious that the infrastructure metrics in test system for cases 3 and 4 are similar to metrics are affected by reconfiguration.

5. CONCLUSION

In current study, a novel approach was presented for exploitation programming due to changes in weather conditions and line outage risk for a sample distribution grid. The studied grid had DG units, ES, isolated switches and DR capabilities. The employed approach is designed in such way which the exploitation programming in unexpected conditions, takes into account the possibility of line outage and its marginal costs, the ability to change the planning and reconfiguration from a purely economic mode to a more resilient mode and the grid with low probability of outages and better resilient in extreme weather conditions could continue its activities with good resilience. The novelty of paper is based on defining new application for DRP, rescheduling of energy resources and reconfiguration by considering probability of outages caused by weather condition. In this regard, results are explaining the different of normal operational planning (without considering weather based outages) and resilient operational planning (with considering weather impact in operational planning and changes in DRP, resource scheduling and reconfiguration).

In the addressed methodology, it is revealed that modern grids can change their operational planning dynamically by considering unplanned definite risks and taking into account costs and profit sharing ability. Unexpected conditions are taken into account considering the wind speed and the number of lightning strikes. Four cases were examined with different approaches to examine grid behavior and resilience and flexibility at time intervals with the probability of definite occurrence. The results showed that the grid operator can use reconfiguration and rescheduling of resources to reduce outages and utilization costs. Objective functions for the power grid and the private sector were simultaneously defined and examined in the framework of multi-objective optimization. Although the definite risk for all four cases was assumed to be the same over time, it was shown that there were significant differences between conventional operational planning and proposed planning in unexpected conditions by comparing $\Phi\Lambda E\Pi$ metrics. The ϵ-constraint method related to the GA was applied to attain Pareto sets and solve the issue of multi-objective optimization trial with intention to use the full potential of the grid so that the private sector could benefit more by fair profit sharing mechanism. Numerical studies have shown with the use of reconfiguration and increasing the proposed price to private sector, in proportion with risk level, we could guarantee the continuity of grid work in unexpected conditions by use of DG and DRP. It was also shown that the characterized load and voltage curve improve under these conditions.

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