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A Robust MPC Method for Post-Disaster Distribution System Reconfiguration based on Repair Crew Routing

Ali Arjomandi-Nezhad[1]
Mahmud Fotuhi-Firuzabad[1,4]

Hesam Mazaheri[2]
Matti Lehtonen[4]

Moein Moeini-Aghtaie[3]
Saeed Peyghami[5]

[1]*Department of Electrical Engineering, Sharif University of Technology*, Tehran, Iran,
[2]*Department of Electrical and Computer Engineering, Texas A&M University*, College Station, TX, USA
[3]*Department of Energy Engineering, Sharif University of Technology*, Tehran, *Iran*
[4]*Electrical Engineering and Automation Department, Aalto University, Espoo, Finland.*
[5]*Department of Energy (AAU Energy), Aalborg University, Aalborg, Denmark*

***Abstract*—Distribution system reconfiguration is an effective solution to reduce the consequences of a disaster through transferring loads to another feeder via automatic switches. Meanwhile, an optimal sequence of damage components repairments provides the operator with the opportunity to utilize components that play a critical role in restoring loads sooner. Motivated by the rise in penetration of renewable distributed generators in modern distribution systems, this paper aims to develop a robust reconfiguration and crew routing co-optimization method to cope with renewable and demand uncertainties while recovering from a disaster. The method optimizes the grid recovery process for the worst load/generation scenario and repeats the optimization every time step considering the activities before the current time step. Finally, a case study on the IEEE 33-bus distribution test network is investigated to analyze the efficiency of the method.**

Keywords— Reconfiguration, model predictive control, outage management.

NOMENCALTURE

A. Sets and Indices

Dmg_i	Set of damaged buses.
Dmg_l	Set of damaged lines.
L	Set of lines.
NL	Set of damaged lines.
SW	Set of switchable lines.
Sb	Set of substation buses.
i, j	Index for buses.
l	Index for lines.
m, n	Index for the place of damaged components and start and end depots.
t	Index for time.

B. Parameters

A_i^{PVmax}	Area of photovoltaic panel installed at bus *i* (m^2).
$e_{i,t}^D$	Demand prediction error at bus *i* and time *t*.
$e_{i,t}^{PV}$	Photovoltaic generation prediction error at bus *i* and time *t*.
M	A big number used in the big-M method
N_i	Number of customers connected to bus *i*.
nc	Number of repair crews
$p_{i,t}^D$	Active power demand at bus *i* and time *t*.
P_l^{max}	Maximum active power at line *l*.
P_i^{DGmax}	Maximum active DG generation at bus *i*.
p_t^{PVmax}	Maximum PV generation density at time *t*.
$P_{i,t}^{PVmax}$	Maximum PV generation at bus *i* and time *t*.
$q_{i,t}^D$	Reactive power demand at bus *i* and time *t*.
Q_l^{max}	Maximum reactive power at line *l*.
Q_i^{DGmax}	Maximum reactive DG generation at bus *i*.
R_l	Resistance of line *l*.
$r_{m,c}$	Repair time duration of component *m* by crew *c*.
re	Metric of recovery agility
S	Number of supplied customers
S_0, S_{pe}	Desired and post-disaster number of supplied customers
$tr_{m,n}$	Route duration from *m* to *n*.
TSD	Time step duration.
w_i	Priority weight of customers which connected to bus *i*.
X_l	Reactance of line *l*.
ε	Maximum voltage deviation.
σ_D	Standard deviation of load prediction error.
σ_{PV}	Standard deviation of PV generation prediction error.

C. Variables

$AT_{n,c}$	The time when repair crew *c* approach damage component *n*.
$f_{m,t}$	Binary variable to consider finishing the repair of damage component *c* at time *t*.
$P_{i,t}^{DG}$	Active DG generation installed at bus *i* and time *t*.
$P_{l,t}$	Active power at line *l* and time *t*.
$Q_{i,t}^{DG}$	Reactive DG generation installed at bus *i* and time *t*.
$Q_{l,t}$	Reactive power at line *l* and time *t*.
$u_{i,t}^G$	Situation of DG installed at bus *i* and time *t*. (1: if the DG is on. 0: if the DG is off.)
$u_{l,t}^L$	Situation of line *l* at time *t* (1: if the line is on.)
$V_{i,t}$	Voltage of bus *i* at time *t*.

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$x_{m,n,c}$	Movement binary variable (1: if crew *c* move toward component *m* after repairing component *n*, immediately)
$y_{m,c}$	The binary variable indicating whether component *m* is repaired by crew *c* or not (1: if it is repaired by crew *c*)
$z_{m,t}$	Availability of component *m* at time *t* (1: if it is available and 0: if is unavailable)
$\beta_{i,j,t}$	Binary variable which is 1 if bus *i* is the parent of bus *j*, according to the definition of the parent in graph theory, at time *t*.
$\rho_{i,t}$	Binary variable which is 1 if customers at bus *i* are supplied at time *t*.

D. Symbols

$\widehat{var}$	Predicted value of general variable *var*.
$\breve{var}$	Real value of general variable *var*.
$\widetilde{var}$	Worst value of general variable *var*.
$\overline{var}$	Value of general variable *var* in optimization of previous time step

I. Introduction

Nowadays, societies are highly dependent on uninterruptable electricity energy supply for many aspects of their lives. Unfortunately, the occurrence of natural disasters such as storms, earthquakes, floods, etc. has threatened the sustainability of the electrical energy systems. An example of which can be considered is the 2018 Hurricane Michael cut out power to 452000 customers in Virginia [1]. Taking lessons from previous disasters, power system engineers and researchers suggested several measures to decrease the consequences of upcoming high impact low probability (HILP) events.

In this vein, two viewpoints, which are operation-oriented and planning-oriented, have been introduced by the researchers to manage the consequences of disasters on power systems [2]. The planning-oriented viewpoint such as storage placement [3] proposes to make the system stronger to better withstand such threats [4]. On the other hand, the operation-oriented viewpoint refers to actions such as outage management which are taken between some hours before the events until the full recovery [5]. In fact, operation-oriented measures suggest making wiser operational decisions to deal with the event. It includes preventive, corrective, and restorative measures which are taken beforehand, at the same time, and after the event; respectively [6]. "Outage management", as a restorative operation-oriented approach, refers to all of the activities to restore the interrupted loads due to the occurrence of events. Outage management, which is usually done by the repair crews and the system operator, follows a multistep procedure. The main outage management activities are damages assessment, repairment, distribution system reconfiguration (DSR), and DG dispatch [7]. Optimizing and coordinating these activities leads to a more agile load restoration. However, finding the optimal recovery procedure is a challenging task, especially if there is a high penetration of renewable energy sources (RES), which causes generation uncertainty in the distribution system.

Several pieces of research in the literature aim to decrease the outage duration through outage management tasks optimization. Authors in [7] present co-optimizing repair crew routing and the reconfiguration procedure to considerably decrease interrupted energy by coordinating the schedule of opening and closing switches, dispatching the DGs, and the sequence of repairing damaged components. All of the mentioned activities can be called "recovery scheduling". In [8], the mobile source routing problem is combined with repair crew routing and distribution system reconfiguration co-optimization to decide on the optimal restoration logistics. None of the mentioned references consider loads' and RESs' uncertainties in outage management. Due to the increase of RES penetration in modern distribution systems, power systems engineers have faced a high degree of uncertainties, resulted from the nature outputs of RES [9]. Thus, in practical cases, the real network load and generation situation may differ from those they have considered in the recovery scheduling step. Therefore, to cope with this pitfall, references [10]-[11] present probabilistic reconfiguration optimization models to consider uncertainties. The rationale behind using the probabilistic approach is the fact that the mean value over many repetitions is near the expected value. However, confronting low probability events, we should be ready for worsts scenarios. Therefore, robust optimization methods are more suitable for natural disasters compared to probabilistic methods which target expected value because the expected value is a good indicator only for credible events.

Motivated by the aforementioned problems, this paper proposes a robust model predictive control (R-MPC) maximize the number of served customers. Unlike presented conventional methods, the proposed optimization model can be repeatedly calculated during the recovery phase in the RMPC; as a result, the recovery strategy can adapt with new information released from uncertainties parameters, i.e. load and RES output during the recovery phase. Therefore, the main contributions of this paper are as follows:

- Proposing an RMPC optimization model to maximize the restored load considering the worst value of load and RES output for future time steps.
- Modifying repair crew routing to be compatible with the RMPC model. In this way, the routing plan can change in every time step, while previous repair actions or movements are fixed.

The rest of this paper is organized as follows. In section 2 represents the conventional outage management formulation, uncertainty modeling, and proposed RMPC framework. After that, numerical results are presented in section 3 to examine the efficiency of the proposed approach. Finally, the conclusion is drawn in section 4.

II. Methodology

Before presenting the proposed framework in Subsection 2.4, the formulation of conventional distribution system reconfiguration and repair crew routing co-optimization based on the model in [7] is presented in the first two following subsections. Then, the uncertainty modeling is discussed in Subsection 2.3. The main goal of the recovery actions is to serve the maximum number of customers and avoid social dissatisfaction and economical losses. Therefore, the objective function (1) is represented as the net number of supplied customers during the recovery process.

$$\max \{ \sum_{\forall t} \sum_{\forall i} w_i . N_i . \rho_{i,t} \} \quad (1)$$

A. Distribution System Reconfiguration

Distribution systems operators can change the configure of the system to agile restoring loads. Nevertheless, changing the configure is constrained to several technical necessities. For example, DGs can generate within a predefined interval, and lines cannot pass more power than their capacity. Equations (2)-(5) represent DGs' and lines' active and reactive power limits. Demands and available generations are equal to the predicted value in the conventional framework. Topological constraints of the distribution system are radially presented in (6)-(9) by spanning tree theory [7]. The demand and generation balance in each bus is presented in (10)-(11). Linear voltage drop approximation is represented in (12)-(13), in which the voltage value of two buses is calculated by the Big-M method. Therefore, equations (12)-(13) will be relaxed when the line is open. Finally, voltage limits are presented in (14) [7].

$$0 \leq P_{i,t}^{DG} \leq P_i^{DGmax} * u_{i,t}^G \quad (2)$$

$$0 \leq Q_{i,t}^{DG} \leq Q_i^{DGmax} * u_{i,t}^G \quad (3)$$

$$-P_l^{max} * u_{l,t}^L \leq P_{l,t} \leq P_l^{max} * u_{l,t}^L \quad (4)$$

$$-Q_l^{max} * u_{l,t}^L \leq Q_{l,t} \leq Q_l^{max} * u_{l,t}^L \quad (5)$$

$$u_{l,t}^L = 1 \qquad l \in L - (SW \cup NL) \quad (6)$$

$$u_{l,t}^L = \beta_{i,j,t} + \beta_{j,i,t} \qquad l \equiv ij \quad (7)$$

$$\beta_{i,j,t} = 0 \qquad j \in Sb \quad (8)$$

$$\sum_{\forall i} \beta_{i,j,t} \leq 1 \qquad \forall j \quad (9)$$

$$\sum_{l \in L(.,i)} P_{l,t} + P_{i,t}^{DG} = \sum_{l \in L(i,.)} P_{l,t} + \rho_{i,t} p_{i,t}^D \qquad \forall i \quad (10)$$

$$\sum_{l \in L(.,i)} Q_{l,t} + Q_{i,t}^{DG} = \sum_{l \in L(i,.)} Q_{l,t} + \rho_{i,t} Q_{i,t}^D \qquad \forall i \quad (11)$$

$$-M(1 - u_{l,t}^L) \leq V_{j,t} - V_{i,t} + \frac{R_l P_{l,t} + X_l Q_{l,t}}{V_1} \quad (12)$$

$$V_{j,t} - V_{i,t} + \frac{R_l P_{l,t} + X_l Q_{l,t}}{V_1} \leq M(1 - u_{l,t}^L) \quad (13)$$

$$1 - \varepsilon \leq V_{i,t} \leq 1 + \varepsilon \quad (14)$$

$$u_{i,t}^G \leq z_{m,t} \quad \forall\, i \in Depend(i,m), i \in Dmg\_i \quad (15)$$

$$u_{l,t}^L \leq z_{m,t} \quad \forall\, i \in Depend(l,m), i \in Dmg\_l \quad (16)$$

Distribution system reconfiguration and repair crew routing problems can be connected by (15)-(16). According to these equations, if damaged component m belongs to line element line l or bus i, the element is unavailable until the end of component m repairment.

B. Repair Crew Routing

If the repair activities are co-optimized with DSR, the components that are more critical in load-serving are taken back to the system sooner. To do so, the repair sequence variables are considered as decision variables of the coordinated DRS and repair crew routing problem. Besides, the following constraints which model repair crew routing are added to the distribution system reconfiguration optimization model.

$$\sum_{\forall n \neq m} x_{m,n,c} - \sum_{\forall n \neq m} x_{n,m,c} = 0 \quad \forall\, c, m \neq start, end \quad (17)$$

$$\sum_{\forall n \neq m} x_{m,n,c} - \sum_{\forall n \neq m} x_{n,m,c} = 1 \quad \forall\, c, m = start, end \quad (18)$$

$$\sum_{\forall c} \sum_{\forall n \neq m} x_{n,m,c} = nc \qquad \forall\, m = end \quad (19)$$

$$\sum_{\forall c} y_{m,c} = 1 \qquad \forall\, m \neq end \quad (20)$$

$$y_{m,c} = \sum_{\forall n \neq m} x_{m,n,c} \qquad \forall m \neq start, end \quad (21)$$

$$AT_{m,c} + r_{m,c} + tr_{m,n} - AT_{n,c} \leq M(1 - x_{m,n,c}) \qquad \forall m \neq \{start, end\}, n \neq m, c \quad (22)$$

$$-M(1 - x_{m,n,c}) \leq AT_{m,c} + r_{m,c} + tr_{m,n} - AT_{n,c} \quad \forall m \neq \{start, end\}, n \neq m, \forall\, c \quad (23)$$

$$\sum_{\forall t} f_{m,t} = 1 \qquad \forall\, m \quad (24)$$

$$\sum_{\forall c} (AT_{m,c} + r_{m,c}) \leq \sum_{\forall t} TSD.t.f_{m,t} \qquad \forall\, m \quad (25)$$

$$\sum_{\forall t} TSD.t.f_{m,t} \leq \sum_{\forall c} (AT_{m,c} + r_{m,c}) - \delta \qquad \forall\, m \quad (26)$$

$$AT_{m,c} \leq y_{m,c}.M \qquad \forall\, m, c \quad (27)$$

$$z_{m,t} = \sum_{t'=1}^{t-1} f_{t'} \qquad \forall\, m, t \quad (28)$$

$$z_{m,t} = 1 \qquad \forall\, m, t = 1 \quad (29)$$

Equations (17)-(29) present the constraints of repair crew routing. Equation (17) ensures that every crew which enters a place will exit from that place unless the place is the start or the end depots. Constraint (18) forces that all crews start from the start depot. All of the crews end their mission into the end depot according to (19). Equation (20) asserts that each damaged component will be repaired by a crew. In equation (21), the relationship between variables $x_{m,n,c}$ and $y_{m,c}$ is asserted. Furthermore, Constraints (22)-(23) computes the repair crews' arrival time to each place. If crew *c* travels from m to *n*, the arrival time to m will be the summation of the duration taken to repair *n*, the arrival time to n, and the travel duration from m to *n*. Constraint (24) says that for each damaged component, there is a time step that the component would be repaired in. Equations (25)-(26) calculate the finishing time step of repairing component m. In these equations, δ is a small number. Also, the arrival time of crew c to a component which is not repaired by crew c is considered zero, shown in (27). A component will be available at time step t if it is repaired in any time step before the t. Based on this fact, equation (28) makes a connection between the availability of the component and its repair finishing time step.

C. Uncertainty modelling

As explained in the Introduction Section, the amount of load and RES power cannot be exactly predicted at the recovery planning stage. As Equations (10) and (11), the values of these variables affect the optimal solution, consequently, the optimal recovery decision. Uncertainty modelling is a prerequisite of robust optimization. This subsection discusses the load and generation uncertainty model. The real values of these variables are defined in (30) and (31). The first parts of these equations are predicted values; while, the second parts are Gaussian errors.

$$\breve{p}^{D}_{i,t} = \bar{p}^{D}_{i,t} + e^{D}_{i,t} . \bar{p}^{D}_{i,t} \qquad (30)$$

$$\breve{p}_t^{PVmax} = \bar{p}_t^{PVmax} + e_t^{PVmax} . \bar{p}_t^{PVmax} \qquad (31)$$

Without losing the generality, it is assumed that distribution systems are geographically small. For bigger systems, the grid can be divided into several parts in which each part of the grid's recovery can be optimized independently of other parts. Solar irradiation to all photovoltaic modules in the geographically small distribution system is equal. However, the amount of photovoltaic generation at bus i depends on the size of the photovoltaic panels. Hence, PV generations are defined as the multiplication of their area and regional solar irradiation as asserted in (32).

$$\breve{P}^{PVmax}_{i,t} = \breve{p}_t^{PVmax} A_i^{PVmax} \qquad (32)$$

The Gaussian probability distribution function is utilized in this paper to consider load error and photovoltaic generation density error [11]. The probability that a normal random variable takes a value more than 3 times of standard deviation is around 0.0013. Similarly, the probability that the variable be less than -3 times of standard deviation is around 0.0013. The worst load and photovoltaic errors are depicted in (33) and (34), respectively with 99.87 percent confidence. These worst errors are considered as the worst case in the proposed robust model in the following subsection.

$$\tilde{e}^{D}_{i,t} = 3\sigma_D \qquad (33)$$

$$\tilde{e}_t^{PVmax} = -3\sigma_{PV} \qquad (34)$$

D. RMPC co-ordinated DSR and repair crew routing

In this section, the proposed uncertainty-aware RMPC distribution system reconfiguration and repair crew routing is introduced. Robust optimizations, in general, aim to optimize the objective function in the worst-case scenario [13]. In the case of DER and load uncertainty-aware recovery optimization, the worst scenario is when demands and generation errors are according to (33) and (34) as discussed in Subsection 2.3. Since the information about demands and generations is updated during the recovery interval, MPC approach [14] in which optimization is repeated until the end of the process is combined with the proposed robust optimization. The proposed RMPC framework is shown in Fig 1. As can be traced in Fig. 1, the joint DSR and repair crew routing optimization is repeatedly recalculated every time step to modify the reconfiguration schedule, conventional DGs dispatches, and repair crew routing based on new information that gets available in the current time step. This information is the exact demand and generation values. DGs dispatch and distribution system reconfiguration can revalue in each action time step, no matter what advisory values they got in previous time steps. The optimal values of the decision variables for future time steps are only advisory. They got updated subsequently. Repair crew routing optimization, however, is not independent of previous time steps optimization because the crews, who either are moving from one place to another place or are doing a repair on one element, cannot change their task in the current time step. To model the inter-temporal relationship of repairs, all of the movements ($x_{m,n,c}$) that start before the current time step should be fixed (35).

$$x_{m,n,c} = fix\_x_{m,n,c} \qquad if(\, fix_{m,n,c} = 1) \qquad (35)$$

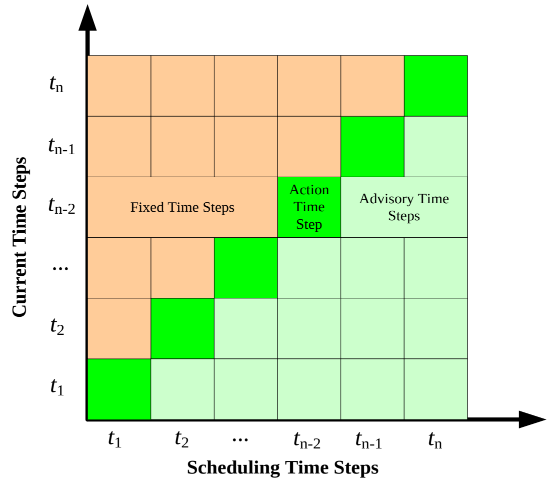

Fig. 1. Proposed framework's schedule structure

The proposed process of RMPC recovery is summarized in **Algorithm 1**. At first, in the scheduling stage, all demands and RES outputs are equal to the worst value according to (33) and (34). Then, in order to reduce the prediction mismatch, demands and RES outputs are adjusted to the real values. The optimization is performed again in every time step. Furthermore, the crews' previous movements are fixed because those movements have already been done and cannot be changed. Only afterward movements can be changed. The method of fixing movements, which determine the fixed movements and their values, is presented in lines (7)-(12) of the presented algorithm. In this paper, $\overline{var}$ is a value of a general variable var of the optimization performed at the previous time step. To check whether a movement started before the current time step, the arriving time of crews to point *m* is subtracted from the travel duration to point *m*. This subtraction gives the time instance at which a crew moved toward pointed *m*. If the result is less than the current time step, all $x_{n,m,c}$ (all movements which end to *m*) are fixed. Finally, the optimization repeats to modify the next hours' recovery plan based on current values of demand and RES output.

Algorithm 1

1: ***Set*** *Current time* = t_1
2: ***Set*** $fix_{m,n,c} = 0$ $\forall\ m, n, c$
3: ***Set*** $p^D_{i,t} = \tilde{p}^D_{i,t}$, $p^{PVmax}_{i,t} = \tilde{P}^{PVmax}_{i,t}$ $\forall\ t$
4: ***Solve*** max (1) Subjected to (2)-(28)
5: ***Set*** $\overline{var} = var$ for all variables
6: ***for*** *Current time* = t_2 : t_n
7: ***for*** *m* = 1: Damaged
8: ***if*** $\sum_{\forall c} \overline{AT_{m,c}} - \sum_{\forall c} \sum_{\forall n} (\overline{tr_{n,m}} . \overline{x_{n,m,c}}) < (Current\ time - 1) * TSD$
9: ***Set*** $fix_{n,m,c} = 1$ $\forall\ n, c$
10: ***Set*** $fix\_x_{n,m,c} = \overline{x_{n,m,c}}$ $\forall\ n, c$
11: ***end if***
12: ***end for***
13: ***Set*** $p^D_{i,t} = \breve{p}^D_{i,t}$, $p^{PVmax}_{i,t} = \breve{p}^{PVmax}_t$; $t \le Current\ time$
14: ***Set*** $p^D_{i,t} = \tilde{p}^D_{i,t}$, $p^{PVmax}_{i,t} = \tilde{p}^{PVmax}_t$; $t > Current\ time$
15: ***Solve*** max (1) Subjected to (2)-(28), (34)

Set $\overline{var} = var$ for all variables
end for

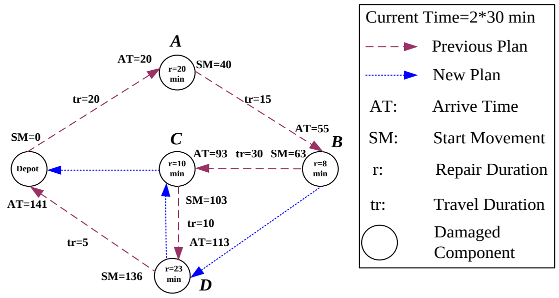

Fig. 2. Routing schedule change during recovery

As shown in Fig 1, the distribution system operator reconfigures the system, re-dispatch the conventional DG, and specifies the route of repair crews based on the optimal values of decision variables in the current time step. The values are advisory for the next time steps. An example of the proposed model has been presented in Fig. 2. The robust optimization procedure is performed before the recovery process. The route (red lines) is considered as the optimal route according to the optimization model. After 60 minutes, the real value of generation and demand have been provided. Then, the optimization model is repeated to correct the repair route, dispatch, and switching based on the newly available information. Note that result of the repeated optimization model cannot change "*Depot to A*" and "*A to B*" due to being provided before one hour. Thus, this part is considered from the old plan; however, route *B to C* can change in the new plan.

III. Case Study

To assess the efficiency of the proposed approach, this method is implemented on the IEEE 33-Bus test network [16]. This test system is presented in Fig. 3. In Table I, nine damaged components are listed. The predicted load profile and the PV generation density prediction, depicted in Fig 4, are similar to [11], [16]. The standard deviation of demand and solar generations are $\sigma_D = 0.03$ and $\sigma_{PV} = 0.05$ respectively [12]. To examine the efficiency of the method, both the conventional load restoration and RMPC are implemented for this case study. Three cases are simulated:

TABLE I. Damaged Components of the Case Study

Component	Repair Duration (hr.)	Component	Repair Duration (hr.)
Node 5	2	Line 10-11	1.5
Node 12	3	Line 2-19	0.4
Node 14	2	Line 28-29	1
Node 28	2	Line 32-33	0.5
Line 2-3	1.1		

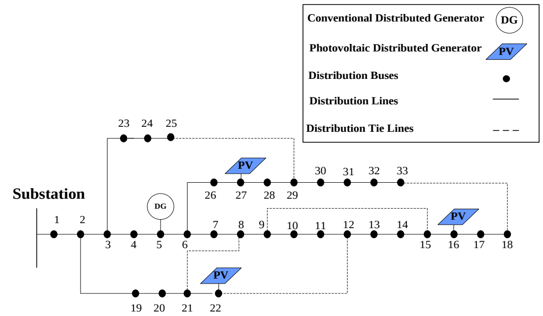

Fig. 3. Modified IEEE 33 buses test network

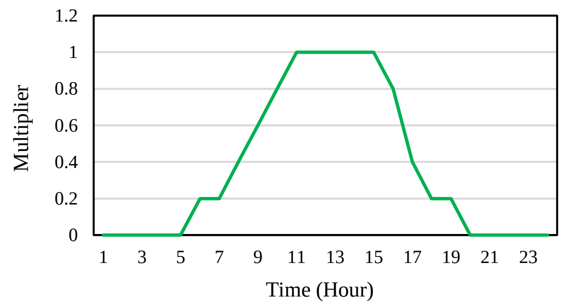

Fig. 4. Predicted PV generation density

- **Case 1 (Based Case):** one conventional DG with (500 kW) at bus 5 and three PV DGs with 500 kW and 600 kW and 750 kW maximum generation are installed at buses 16, 22, and 27, respectively. (Following Fig. 3.)
- **Case 2:** All DGs in the network are renewable at buses 5, 16, 22, and 27 with 500 kW, 500 kW, 600 kW, and 750 kW maximum generation, respectively.
- **Case 3:** two conventional DGs with the capacity of 500 kW and 750 kW at buses 5 and 27 and two PV DG with 500 kW and 600 kW maximum generation are installed at buses 16 and 22, respectively.

The programs are run by CPLEX/GAMS solver on a personal computer (PC) with an Intel Core i5 CPU and 6 GB RAM.

IV. Results

To check the effectiveness of the proposed outage management method, the metric which is introduced in [17] is employed. According to this metric, the agility of a recovery process is defined as “the number of recovered customers divided by the average outage time of the affected customers.” It is asserted as (35).

$$re = (S_0 - S_{pe}) / \left[\frac{\int_{S_{pe}}^{S_0} S dt}{S_0 - S_{pe}} \right] \quad (35)$$

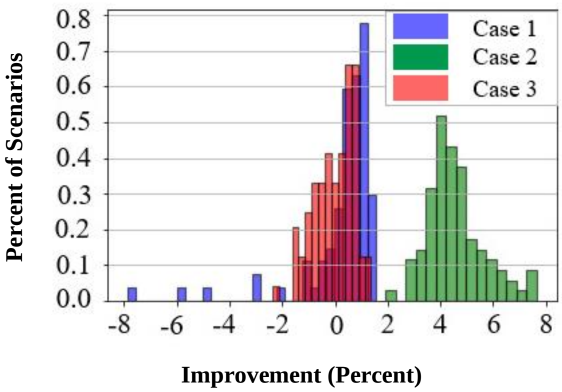

Fig. 5. Improvement in net number of supplied customers,

The interested readers are referred to [17] for more information about this metric.

The results are presented in Fig. 5. As can be seen, for the base case, the number of served customers in most of the scenarios enhances slightly. Only in a few scenarios, the number of supplied customers are decreased compare to that of the conventional method. The result of case 2 and case 3 differs significantly. In case 2, in which all DGs are renewable, the improvement in load-serving is considerably more. This is mainly because of the fact that uncertainty is higher in case 2, and uncertainty aware approaches is more necessitated. However, in case 3, the less renewable DG case, the proposed model does not make a significant change in load-serving. On average, improvements in load-serving are 0.285 %, 4.556 %, and -0.045% for case 1, case 2, and case 3 respectively. Therefore, for a system with a low level of RES penetration, the proposed method does not affect the metric substantially. However, the results highlight the fact that the proposed method is an effective outage management optimization for networks with a high installed renewable DG capacity.

To further examine the proposed method, the values of the metric, mentioned in the previous subsection, for the three cases are computed. The averages of the metric are presented in Table 2. The results support the claim that the proposed method enhances the metric in case of high renewable energy sources penetration.

TABLE II. DAMAGED COMPONENTS OF THE CASE STUDY

Case	Conventional Method	Proposed Method	Improvement (Percent)
Case 1	281.17	286.48	1.9
Case 2	235.96	289.07	22.5
Case 3	272.61	276.52	1.43

V. CONCLUSION

This paper developed a robust predictive control distribution system recovery method to cope with the load and renewable generation uncertainty challenges. In the scheduling step, the recovery procedure has been optimized for the worst scenario. Then, the co-optimization repeats every time step to correct the schedule based on the new information of generations and demands. Since the repair action done in previous time steps affect the rest of the recovery procedure, the history of repair crews' activities, which has already been done, is fixed in the current time step optimization. The discussed methodology has been compared with the conventional method, developed in research papers, in the case study. Results reveal that the proposed method cause improvement in the number of supplied customers in the majority of scenarios. The more renewable penetration, the more substantial effect on the proposed model.

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