Enhancing Distribution Grid Resilience Through Model Predictive Controller Enabled Prioritized Load Restoration Strategy

Preprint

Abinet Tesfaye Eseye, Xiangyu Zhang, Bernard Knueven, and Wesley Jones

National Renewable Energy Laboratory

Presented at the 52nd North American Power Symposium
April 11-14, 2021

NREL is a national laboratory of the U.S. Department of Energy
Office of Energy Efficiency & Renewable Energy
Operated by the Alliance for Sustainable Energy, LLC

This report is available at no cost from the National Renewable Energy Laboratory (NREL) at www.nrel.gov/publications.

Contract No. DE-AC36-08GO28308

Conference Paper
NREL/CP-2C00-77124
February 2021

Enhancing Distribution Grid Resilience Through Model Predictive Controller Enabled Prioritized Load Restoration Strategy

Preprint

Abinet Tesfaye Eseye, Xiangyu Zhang, Bernard Knueven, and Wesley Jones

National Renewable Energy Laboratory

Suggested Citation
Eseye, Abinet Tesfaye, Xiangyu Zhang, Bernard Knueven, and Wesley Jones. 2021. *Enhancing Distribution Grid Resilience Through Model Predictive Controller Enabled Prioritized Load Restoration Strategy: Preprint*. Golden, CO: National Renewable Energy Laboratory. NREL/CP-2C00-77124. https://www.nrel.gov/docs/fy21osti/77124.pdf.

NREL is a national laboratory of the U.S. Department of Energy
Office of Energy Efficiency & Renewable Energy
Operated by the Alliance for Sustainable Energy, LLC

This report is available at no cost from the National Renewable Energy Laboratory (NREL) at www.nrel.gov/publications.

Contract No. DE-AC36-08GO28308

Conference Paper
NREL/CP-2C00-77124
February 2021

National Renewable Energy Laboratory
15013 Denver West Parkway
Golden, CO 80401
303-275-3000 • www.nrel.gov

Cover Photos by Dennis Schroeder: (clockwise, left to right) NREL 51934, NREL 45897, NREL 42160, NREL 45891, NREL 48097, NREL 46526.

NREL prints on paper that contains recycled content.

Enhancing Distribution Grid Resilience Through Model Predictive Controller Enabled Prioritized Load Restoration Strategy

Abinet Tesfaye Eseye, Xiangyu Zhang, Bernard Knueven, Wesley Jones
Computational Science Center
National Renewable Energy Laboratory (NREL)
Golden, Colorado, USA 80401
AbinetTesfaye.Eseye, Xiangyu.Zhang, Bernard.Knueven, Wesley.Jones@nrel.gov

***Abstract*—Effective resilience improvement strategies enable the power grid to cope with disruptive extreme events. Most power grid outages are caused by disruptions in distribution grids. Motivated by the urgent need for power system resilience research, this paper proposes a priority-weighted optimal load restoration technique to enhance the resilience of distribution grids against extreme events. The proposed technique is based on smart distribution technology and framed as sequential multi-step decision process (MDP) and mixed integer linear program (MILP). It is formulated as optimal control problem with a model predictive control (MPC) approach. We applied the devised MILP-MPC-based load restoration technique to a simplified single-bus version of the IEEE 13-bus distribution system with integrated distributed energy resources (DERs) such as wind turbine, photovoltaic array, microturbine, and energy storage device. The technique executes a reducing and rolling horizon optimization in each control step in real-time using the forecasted information of the renewables, the fuel status of the microturbine and the state of charge of the energy storage device. We consider an extreme event which triggered outage of the upstream utility grid and caused islanded operation of the distribution grid. We demonstrated the effectiveness of the proposed MPC approach in restoring the distribution grid loads based on their priority during the main grid outage-caused islanded operation.**

***Index Terms*--Distribution grid, DER, extreme event, load restoration, model predictive controller, resilience.**

I. Introduction

The electricity grid is the base for the current human civilization, and its resilient and secure operation is essential to our lives in many dimensions.

This work was authored by the National Renewable Energy Laboratory, operated by Alliance for Sustainable Energy, LLC, for the U.S. Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. Funding provided by the DOE Office of Electricity (OE) Advanced Grid Modeling program. The views expressed in the article do not necessarily represent the views of the DOE or the U.S. Government. The U.S. Government retains and the publisher, by accepting the article for publication, acknowledges that the U.S. Government retains a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this work, or allow others to do so, for U.S. Government purposes.

Although methods, metrics and tools for mitigating unlikely but not rare disruption events in power systems such as failure or malfunction of single system components have been well established and adopted, there is still much to do for rare and high consequence extreme events that may occur in power grids such as natural disasters, cyber-attacks and terrorist attacks [1]. Even though there is no standard definition for resilience, the U.S. Presidential Policy Directive 21 (PPD-21) for Critical Infrastructure Security and Resilience defined resilience as "the ability to prepare for and adapt to changing conditions and withstand and recover rapidly from disruptions."

The incidence of low-probability and high-impact extreme events is rising globally due to the changes in weather conditions and socio-political threats. For example, among the 2500 major outages the U.S. electric utilities have reported to the U.S. Department of Energy (DOE) since 2002, almost half of them (1172) were caused by extreme weather conditions such as storms, hurricanes and unspecified severe weather [2]. That is a mean of 65 weather-related outages per annum. An aggregate of 211 million customers have lost electricity since 2002 in weather-related disruptions across the entire nation. In addition, 17 power transformers were struck by gunfire at the Metcalf Transmission Substation in California in 2013, indicating that the electricity grid is also vulnerable to terrorist attacks [1]. As a cyber-physical system with increasing trends in distributed control and automation of systems, the power grid's cyber-attack surface has also increased. Thus, confronting the rising threats and complexity of the electricity network, establishing resilience into the power infrastructure is a challenging task. While better disruption-proof installation standards should be used to harden the power grid, a complete upgrading of the entire grid is prohibitively expensive. As an option, the idea of power system resiliency is put forth as a remedy to handle the unlikely and high-consequence extreme incidents.

Historic data collected by utilities show that about 90% of the electric grid outages have their origins in the distribution grid [1], [3].

Thus, several research efforts focus on distribution grids [3]. Many researches have been conducted on improving the resilience of the electricity distribution systems. We classified these studies into three categorifies with regard to the problem they examined and the approach they used.

The first category involves the intelligent power management of distribution systems with distribution generations (DGs). This includes a multi-agent system (MAS)-based approach for the economic dispatch of DGs to enforce voltage regulation of the distribution grid [4] and to ensure the supply-demand balance and optimize system efficiency and economy [5], and a model predictive control (MPC) technique to control the real and reactive powers of DGs to regulate system voltage and frequency in distribution grid [6]. Though the electricity delivery to consumers following the utility grid outage mainly depends on the DGs, the stochasticity of the electricity demands and the power generation of the non-controllable DGs were not completely addressed in this category of studies.

The second category involves the formulation and application of stochastic approaches in distribution systems. This includes a scenario-based stochastic strategy to minimize the running expense of islanded microgrids (MGs) [7] and a scenario tree-based technique to balance uncertain supply and demand with optimal management of energy storage devices and minimal wind power curtailment and load shedding [8].

The resilience improvement strategies in the above two categories were designed for normal distribution system operating conditions without taking into account the restoration potential of a distribution grid following the occurrence of disruptive event(s).

The third category involves automatic restoration (self-healing) approaches for distribution systems following extreme events. This includes a formulation of a priority-weighted load pick up mixed-integer second order cone (MISOC) program [1], an agent-based paradigm for the restorative protection scheme with a graph theory-based expert system [9], a quantifiable decision making approach for distribution grid restoration by sorting restoration plans based on their performance metrics [10], and sectionalization of distribution systems into microgrids [11].

Most of the above studies considered single-step decisions and they did not either consider the integration of renewable energy resources (RESs) into the distribution network or manage the uncertainties of the RES power outputs. However, single-step decisions do not ensure sustainable system resilience over longer operating periods (for example, a few hours ahead). In addition, due to the recent power system design and control paradigm shift towards decentralized architectures, distributed RESs are rapidly being deployed in distribution grids and therefore resilient restoration strategies should look into them.

This paper emphasizes that quick and optimal restoration is a key strategy to enhance the resilience of distribution grids, and resilience improvement approaches for distribution systems are more urgently required. We propose an MPC-enabled prioritized load restoration strategy for distribution grids to improve the grid resilience through the control of dispatchable distributed energy resources (DERs) and seamless islanding following the incidence of extreme events and the identification of the faults.

The devised load restoration formulation is a multi-step sequential decision process which employs the predicted values of the future power outputs of the distributed RESs in the distribution system through the incorporation of renewable power forecasting techniques. The proposed strategy is validated in a simplified version of the IEEE distribution test system.

The remaining sections of the paper are outlined as follows. The devised priority weighted load restoration strategy is discussed in Section II. Section III presents the elements and optimization formulations of the MPC which enables the proposed load restoration technique. The case study and research findings are elaborated in Section IV, and conclusion and future work are given in Section V.

II. PROPOSED PRIORITIZED LOAD RESTORATION STRATEGY

Load restoration aims to maintain service to the maximum possible number of loads following the incidence of an extreme event. It is one of the operational resilience improvement strategies. An effective restoration strategy should serve the loads based on their priority order. Critical loads in the distribution grid such as hospitals are assigned the highest priority in the formulation of the restoration strategy. The restoration process should recover the system performance to a steady state operating condition within an acceptable time frame and at low cost. A resilient distribution system should resist and absorb extreme events and return to near-normal operation quickly.

In this paper, we propose an optimal load restoration strategy following the upstream utility grid outage. The major contributions of the devised strategy are as follows.

1) The distribution grid can be operated in islanding mode following the upstream grid outage through the optimal control of the integrated DERs.
2) The priority of loads is considered. That is, critical loads are recovered first.
3) The restoration process is formulated via a dynamic (shrinking) horizon MPC taking into account the predicted power information of the RESs with augmented forecasting methods.

When line faults occur close to the point of connection (POC) between the distribution system and upstream utility network due to hurricane or earthquake, the system will seamlessly transfer to islanded operation and the load restoration algorithm is activated immediately. During the islanded operation, the MPC optimally coordinates the dispatchable resources (microturbine and energy storage device) and the renewable DGs (wind and photovoltaic solar) to sustain the power delivery service to the maximum possible number of customers based on their priority.

The proposed restoration technique considered the assumptions below: 1) seamless islanding happens automatically during the upstream utility grid outage; 2) the distribution network (power flow) constraints are not considered and hence the system is simplified to a single-bus system with all the generators and loads coupled at a single node; and 3) six-hour service recovery time, that is, the upstream utility grid outage is recovered after six hours of islanded operation. The elements and optimization formulations of the MPC which enables the proposed load restoration strategy is presented in the section below.

III. MODEL PREDICTIVE CONTROLLER (MPC)

There has been considerable research focus in employing MPC for distribution grids with distributed energy resources (DERs) [12]. MPC is an effective approach to formulate load restoration problems if there exist system uncertainty and multi-step sequential decision is required. The objective function and constraints are expressed with a finite-time optimal control problem. The MPC setup we proposed for the load restoration problem has dynamic control horizon which shrinks at each control step by one until the presumed system recovery time. At each control step, a group of system states are updated, the optimal control problem is solved on the fly, the immediate step decisions are applied, and the other decisions are discarded. The MPC control horizon then shifts forward one step in time. We assume a six-hour initial control horizon with five-minute time resolution. Fig. 1 demonstrates the proposed MPC reducing- and rolling-horizon optimization process.

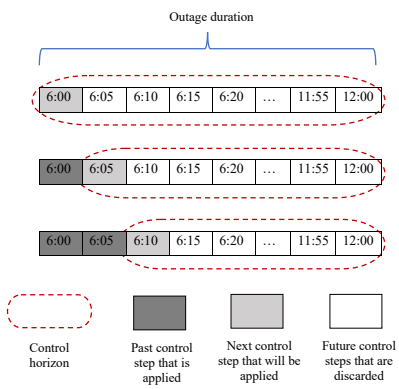

Fig. 1. Reducing- and rolling-horizon optimization.

The proposed MPC-based restoration technique consists of two cascaded modules, the prediction module and optimization module, as shown in Fig. 2. The prediction module contains short-term wind and solar power forecasting methods, while the optimization module executes the reducing- and rolling-horizon optimization illustrated in Fig. 1 and returns the optimal control actions based on the input information from the prediction module and other system operating conditions.

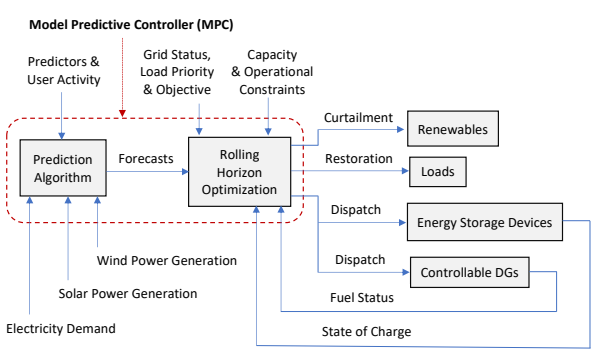

Fig. 2. Control architecture of the proposed MPC.

As forecasting is not the main focus of this paper, we have not developed advanced and very accurate methods for predicting the outputs of the renewables. However, for the sake of having updated estimates of the renewables at each control step of the optimization horizon we have implemented simple prediction methods as presented in the first two subsections below.

A. Wind Power Forecast

We employed a short-term (day-ahead) recursive multi-step time series forecasting technique [13] to predict the power output of the wind turbine (WT) integrated in the case study distribution grid. The technique is simple as it needs few parameters to tune and does not require exogenous set of predictors. With a supervised machine learning model M and n number of prior inputs, the wind power forecast time series $P_t^w = [p_{t+1}^w, p_{t+2}^w, \dots, p_{t+k}^w]$ is given as follows.

$$\begin{aligned} p_{t+1}^w &= M(p_t^w, p_{t-1}^w, p_{t-2}^w, \dots, p_{t-n+1}^w) \\ p_{t+2}^w &= M(p_{t+1}^w, p_t^w, p_{t-1}^w, \dots, p_{t-n+2}^w) \\ &\dots \\ p_{t+k}^w &= M(p_{t+k-1}^w, p_{t+k-2}^w, \dots, p_{t-n+k}^w) \end{aligned} \tag{1}$$

B. Solar Power Forecast

In order to forecast the power output of the PV system integrated in the case study distribution grid, we used a simple retrospective approach: the output from the prior day is used to model the output for the next day with an adjustment, e.g., the predicted PV output for 9 a.m. today is the historical PV output from 9 a.m. yesterday, plus a calculated near-term adjustment. Mathematically, at prediction time t, we measure the forecast error from the prior hour by comparing the actual PV output for the prior hour to the actual PV output for the prior hour from the prior day. We use this measured forecast error to adjust the predicted PV output for the following three hours in a receding fashion. This method is straightforward to implement for the purposes of demonstration and avoids some complications when creating look-ahead PV forecasts [14].

C. Loads

Distribution systems can contain either spot or distributed loads or both. The case study distribution grid contains 10 spot loads. We assumed constant-power load model and time-invariant time series for these loads.

D. MPC Formulations

Here, we present the mathematical formulations of the proposed MPC based on its aforementioned desired functions for the load restoration task. To ensure the distribution system resilience, the proposed MPC aims to maximize the total prioritized restored load (first term in (1)), penalize shedding restored load (second term in (2)), and penalize renewable power curtailments (third and fourth terms in (2)), over the control horizon.

As far as we have investigated, the proposed MPC formulation is novel considering the following aspects:

- We formulated the MPC's rolling-horizon optimization over a shrinking horizon (T in (2)) which decreases by one as the control step (t) forwards by one in time. This helps the distribution system to effectively utilize the DERs for the restoration task in the remaining control steps of the presumed service recovery time.

- The formulated MPC considered penalty for gradual increase in load shedding (second term in (2)). That is, at each control step, shedding an already restored load in the previous times is not allowed (or causes penalty). This assists the distribution grid to sustain the electricity supply to its customers.

Thus, the objective function is defined as follows.

$$Max: \left\{ \sum_{i\in N}\sum_{t\in T} \omega_i . P_{i,t}^{l} - \psi \sum_{i\in N}\sum_{t\in T\setminus\{1\}} \omega_i . max\left(\left(P_{i,t-1}^{l} - P_{i,t}^{l}\right), 0\right) - \alpha \sum_{t\in T} P_t^{wt,cut} - \beta \sum_{t\in T} P_t^{pv,cut} \right\} \quad (2)$$

where, N is the number of loads (load buses), T is the control horizon, i is the node/load index, t is the control step index, ω is the priority weight of load at node i, ψ is the penalty for shedding restored load, α is the penalty for wind power curtailment, β is the penalty for PV power curtailment, $P_{i,t}^{l}$ is the restored load at node i and time t, $P_t^{wt,cut}$ is the wind power curtailed at time t, and $P_t^{pv,cut}$ is the PV power curtailed at time t. Note that as shown in Fig. 1 the control horizon T in (2) shrinks as the MPC recedes forward in time.

While maximizing (2), the objective function is subject to the following constraints: power balance constraint (3), generator capacity limits (4), generator fuel (total energy production) constraint (5), restored load limits (6), energy storage power limits (7)-(9), energy storage state of charge (SOC) limits (10), SOC dynamics (11), and renewable power curtailment limits (12)-(13). Constraint (5) indicates that the microturbine total energy production is limited by its available fuel. Constraints (7)-(9) ensure that the energy storage cannot simultaneously charge and discharge at time t.

$$P_t^{wt} + P_t^{pv} + P_t^{mt} + P_t^{es,dch} = P_t^{wt,cut} + P_t^{pv,cut} + P_t^{es,ch} + \sum_{i\in N} P_{i,t}^{l} \quad (3)$$

$$0 \le P_t^{mt} \le P_{max}^{mt} \quad (4)$$

$$\sum_{t\in T} P_t^{mt} . \Delta t \le E_{max}^{mt} \quad (5)$$

$$0 \le P_{i,t}^{l} \le P_{i,t}^{l,demand} \quad (6)$$

$$0 \le P_t^{es,ch} \le b_t^{es,ch} P_{max}^{es,ch} \quad (7)$$

$$0 \le P_t^{es,dch} \le b_t^{es,dch} P_{max}^{es,dch} \quad (8)$$

$$b_t^{es,ch} + b_t^{es,dch} = 1 , b_t^{es,ch}, b_t^{es,dch} \in \{0,1\} \quad (9)$$

$$SOC_{min}^{es} \le SOC_t^{es} \le SOC_{max}^{es} \quad (10)$$

$$SOC_t^{es} = SOC_{t-1}^{es} + \left(\frac{\eta^{es,ch} P_t^{es,ch}}{C_{es}} - \frac{P_t^{es,dch}}{\eta^{es,dch} C_{es}}\right) \Delta t \quad (11)$$

$$0 \le P_t^{wt,cut} \le P_t^{wt} \quad (12)$$

$$0 \le P_t^{pv,cut} \le P_t^{pv} \quad (13)$$

where, P_t^{wt} is the wind power forecast at time t, P_t^{pv} is the PV power forecast at time t, P_t^{mt} is the microturbine output power at time t, and $P_t^{es,ch}$ and $P_t^{es,dch}$ are respectively the energy storage charging and discharging powers at time t, P_{max}^{mt} is the rated output power of the microturbine, E_{max}^{mt} is the microturbine allowable peak total energy production, Δt is the length of one control step, $P_{i,t}^{l,demand}$ is the demanded load (before the extreme event) at node i and time t, $P_{max}^{es,ch}$ and $P_{max}^{es,dch}$ are respectively the charging and discharging rated powers of the energy storage, $b_t^{es,ch}$ and $b_t^{es,dch}$ are binary variables indicating the status of the energy storage and take a value of 1 respectively if the energy storage is charging and discharging at time t, and 0 otherwise, SOC_t^{es} is the SOC of the energy storage at time t, SOC_{min}^{es} and SOC_{max}^{es} are respectively the allowable minimum and maximum SOCs, and $\eta^{es,ch}$, $\eta^{es,dch}$ and C_{es} are respectively the charging efficiency, discharging efficiency and rated storage capacity of the energy storage device.

The "max" penalty in the second term of (2) makes the objective function non-smooth. To address this, we reformulated the "max" penalty by introducing a slack variable $\mu_{i,t}$ that will represent $max\left(\left(P_{i,t-1}^{l} - . P_{i,t}^{l}\right), 0\right)$ in the solution. Therefore, the objective function (2) can be rewritten as follows:

$$Max: \left\{ \sum_{i\in N}\sum_{t\in T} \omega_i . P_{i,t}^{l} - \psi \sum_{i\in N}\sum_{t\in T} \omega_i . \mu_{i,t} - \alpha \sum_{t\in T} P_t^{wt,cut} - \beta \sum_{t\in T} P_t^{pv,cut} \right\} \quad (14)$$

And, the new constraints for the slack variable are given by:

$$\mu_{i,t} \ge 0 \quad (15)$$

$$\mu_{i,t} \ge P_{i,t-1}^{l} - P_{i,t}^{l}, \ t > 1 \quad (16)$$

The decision variables are therefore: $P_{i,t}^{l}$, P_t^{mt}, $P_t^{wt,cut}$, $P_t^{pv,cut}$, $P_t^{es,ch}$, $P_t^{es,dch}$, SOC_t^{es}, $b_t^{es,ch}$, and $b_t^{es,dch}$. In addition, as it can be seen from the formulated objective function (14) and constraints (3)-(13) and (15)-(16) above, the proposed MPC optimization problem is a MILP. Hence, open-source MILP solvers can be leveraged to find (near) optimal solutions to the proposed MPC optimization problem.

IV. CASE STUDY AND DISCUSSION

The proposed MPC-based load restoration technique is applied to a simplified single-bus equivalent of the IEEE 13-bus distribution system disregarding the network flows and voltage constraints, as show in Fig 3.

We call this system as the *case study system,* hereafter. We considered 10 spot loads (Load1 – Load10) with constant power load models. As shown in Fig. 3, wind turbine (WT), PV array, microturbine (MT), and energy storage (ES) DERs are integrated in the case study system. Table I provides the parameters of case study system.

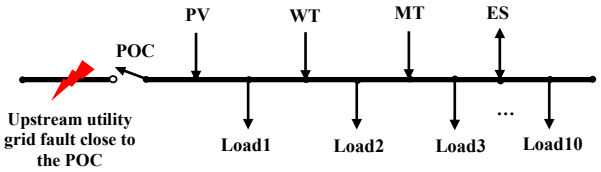

Fig. 3. Case study system.

An extreme event triggered fault in the upstream utility grid close to the point of connection (POC), as shown in Fig. 3, is considered. This caused the utility grid outage and the system immediately switched to islanded operation. The utility grid service recovery time is set as six hours.

TABLE I

SYSTEM PARAMETERS

Parameter	Unit	Value
Load priority weight (ω)	-	[1.0, 1.0, 0.9, 0.85, 0.8, 0.65, 0.45, 0.4, 0.3, 0.3]
Demanded spot loads ($P^{l,demand}$)	kW	[33, 34, 8.5, 85, 60, 60, 58, 115, 64, 85]
Initial control horizon (T_0)	hour	6
Control steps (t)	-	[1, 2, ..., 72]
WT rating	kW	150
PV array rating	kW	300
Penalty factors for WT and PV curtailment (α, β)	-	0.2
Penalty factor for shedding restored load (ψ)	-	100
MT rated power (P_{max}^{mt})	kW	300
MT allowable total energy production (E_{max}^{mt})	kWh	1000
Length of one control step (Δt)	hour	1/12
ES peak charging and discharging powers ($P_{max}^{es,ch}$, $P_{max}^{es,dch}$)	kW	200
ES initial SOC (SOC_0^{es})	%	90
ES charging and discharging efficiencies ($\eta^{es,ch}, \eta^{es,dch}$)	%	95, 90
ES min and max SOCs (SOC_{min}^{es}, SOC_{max}^{es})	%	20, 90
ES rated capacity (C_{es})	kWh	800

The MPC optimization problem was implemented using JuMP in Julia 1.4 and the renewable power forecasting, data analytics, and the MPC execution were implemented in Python 3.7. The computation was carried out on a Mac Pro with Intel Core i7 Quad-Core Processor (2.80GHz) and 16GB RAM, and the problem was solved by the GLPK open source solver.

The case study helps as a prototype example to confirm the significance of deploying DERs and adopting robust distribution grid automations (such as automatic load restoration algorithms as proposed in this work) in enhancing the resilience of power systems against extreme events.

We tested the MPC over 50 scenarios (different fault occurrence times and renewable generation profiles). Due to limitation of space and for the purpose of demonstration, the MPC actions for a single scenario (fault occurrence time = 12:00) on a specific day (August 3, 2019) are illustrated in Figs. 4-7. Fig. 4 shows the aggregate restored load and the resource dispatches over time.

As shown in Fig. 4, the microturbine and storage operates complimentary to each other to serve the loads together with the wind and PV. The storage charges and stores energy in some of the control steps (17:00 – 17:30) to serve more loads in the remaining steps. The total load was restored to full demand (600kW) during the last control steps (17:45 – 18:00).

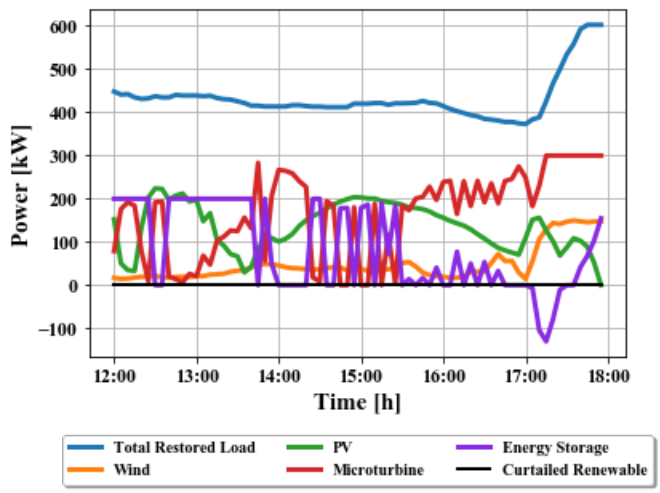

Fig. 4. Load restoration and resource dispatching.

The remaining energy of the controllable DERs over time is shown in Fig. 5. As demonstrated in Fig. 5, the MPC was able to effectively utilize the controllable resources to serve the loads following the occurrence of the extreme event. At the end of the control horizon (18:00), the microturbine was out of fuel (zero remaining energy) and the energy storage reached its minimum SOC (160kWh).

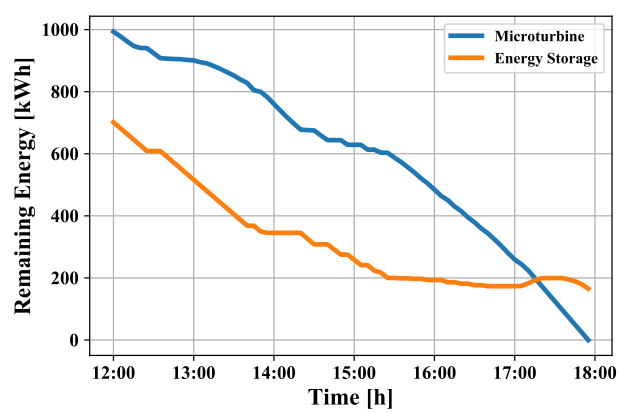

Fig. 5. Remaining energy of the controllable DERs.

The restored load at each node is depicted in Fig. 6, and the demanded versus served energy per node is illustrated in Fig. 7.

As illustrated in Fig. 6, the first 7 higher priority loads (Load1 – Load7) were restored with their full demand (100%) throughout the control horizon. However, the lower priority load (Load8) was served less than its full demand except in the control steps (17:20 – 18:00). Moreover, the lowest priority loads (Load9 – Load10) were not served at all throughout the control horizon except during (17:40 – 18:00) and (17:45 – 18:00), respectively. Similarly, as shown in Fig. 7, the total restored energy over the control horizon is equal to the total demanded energy for the first seven higher priority nodes (loads) and hence the total shedded energy was zero for these nodes. The served energy for the lower priority nodes (last three loads) is less than their demanded energy and thus their unserved energy was higher. This demonstrates the effectiveness of the devised MPC approach for the proposed prioritized load restoration problem.

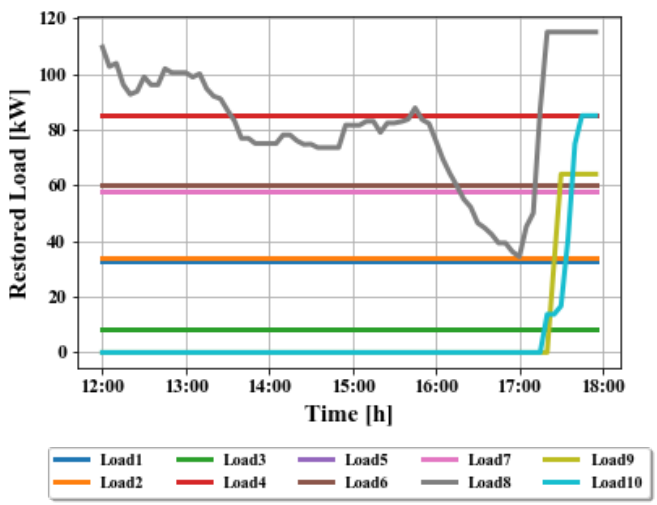

Fig. 6. Restored loads.

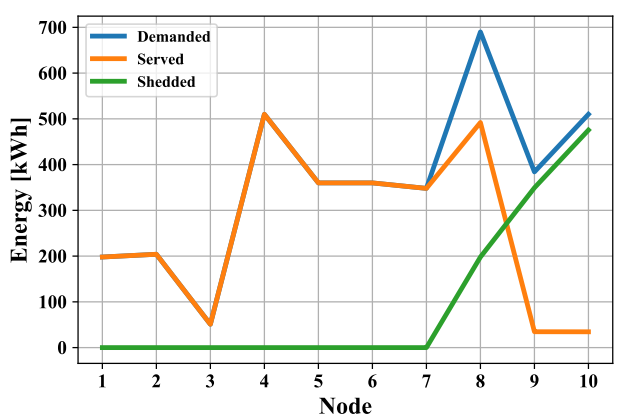

Fig. 7. Demanded versus served energy per node.

V. CONCLUSION AND FUTURE WORKS

The formation of resilient systems and the enhancement of operational resilience have become basic needs for energy systems. During the incidence of extreme events, resiliency is identified as a vital property of critical systems and the community.

To enhance resilience, we devised an optimal and efficient MPC-based load restoration technique and demonstrated its effectiveness using a simplified single-bus version of the IEEE 13-bus distribution system with DERs. We must be aware of that resilience studies are just starting, and disruptive extreme incidents will continue to be challenging to the energy industry and the community. More investments, regulations, novel technologies and practices are greatly required to triumph resilience in the electricity grid. The current research findings and capabilities will continue in the next phases of our research such as incorporating the distribution network flows and voltage constraints in the MPC formulations, consideration of more complex power networks with higher number of nodes and DERs and stochastic MPC formulations to address the uncertainty of the service recovery time and renewables in a better way.

REFERENCES

[1] Z. Bie, Y. Lin, G. Lin. and F.Li, "Battling the Extreme: A Study on the Power System Resilience," *in Proc. of the IEEE*, Vol. 105, No. 7, pp. 1253-1266, July 2017.

[2] Climate Impacts, *E&E News*, October 2019. Available: https://www.eenews.net/stories/1061245945

[3] Enhancing Distribution Resiliency: Opportunities for Applying Innovative Technologies, *Elec. Pow. Research Inst.*, Palo Alto, CA, USA, 2013.

[4] M.E. Baran. and I.M. El-Markabi, "A multiagent-based dispatching scheme for distributed generators for voltage support on distribution feeders," *IEEE Trans. Pow. Sys.*, vol. 22, no. 1, pp. 52–59, Feb. 2007.

[5] F. Ren, M. Zhang, and D. Sutanto, "A multi-agent solution to distribution system management by considering distributed generators," *IEEE Trans. Pow. Sys.,* vol. 28, no. 2, pp. 1442–1451, May 2013.

[6] M. Falahi, S. Lotfifard, M. Ehsani, and K. Butler-Purry, "Dynamic model predictive-based energy management of DG integrated distribution systems," *IEEE Trans. Pow. Del.*, vol. 28, no. 4, pp. 2217–2227, Oct. 2013.

[7] A. Sobu and G. Wu, "Optimal operation planning method for isolated microgrid considering uncertainties of renewable power generations and load demand," *in Proc. 2012 IEEE ISGT Asia*, May 2012, pp. 1–6.

[8] J. Wu and X. Guan, "A stochastic matching mechanism for wind generation dispatch and load shedding allocation in microgrid," *in Proc. 2014 IEEE PES ISGT*, Feb. 2014, pp. 1–5.

[9] S. Sheng, K.K Li, W.L. Chan, Z. Xiangjun, and D. Xianzhong, "Agent-based self-healing protection system," *IEEE Trans. Pow. Del.*, vol.21, no. 2, pp. 610–618, Apr. 2006.

[10] W-H. Chen, "Quantitative decision-making model for distribution system restoration," *IEEE Trans. Pow. Sys.*, vol. 25, no. 1, pp.313–321, Feb. 2010.

[11] Z. Wang and J. Wang, "Self-Healing Resilient Distribution Systems Based on Sectionalization Into Microgrids," *IEEE Trans. on pow. Sys.*, vol. 30, no. 6, Nov. 2015.

[12] T. Morstyn, B. Hredzak and V. G. Agelidis., "Control strategies for microgrids with distributed energy storage systems: An overview," *IEEE Trans. Smart Grid*, vol. 9, issue 4, July 2018.

[13] S.B. Taieb and G. Bontempi, "Recursive multi-step time series forecasting by perturbing data," *in Proc. the IEEE 11th Int. conf. on Data Mining*, Dec. 2011.

[14] D.L. Woodruff, J. Deride, A. Staid, J-P. Watson, G. Slevogt, and C. Silva-Monroy, "Constructing probabilistic scenarios for wide-area solar power generation," *Solar Energy*, 160:153–167, 2018.