

A Feature based Distributed Machine Learning for Post Fault Restoration of a Microgrid Under Different Stochastic Scenarios

Miftah Al Karim, Jonathan Currie, Tek-Tjing Lie

Abstract—Stochastic nature of a large scale wind power plant in a power system with insufficient load margin has significant impact on a post fault network. Such probabilistic character of a system makes it quite a challenge to maintain post fault system stability. A short circuit fault under such contingency may introduce power system oscillation resulting in massive voltage fluctuations. One probable solution is to develop a corrective voltage control (CVC) framework in order to maintain sufficient load margin. Standard CVC measures are based on active and reactive dispatch from generating units. However, in a post contingent scenario it is often critical to select appropriate parameters for CVC. This study implements an offline-online data analysis approach using feature selection and machine learning algorithms, as a mean to develop an accurate CVC framework based on supervisory machine control.

I. INTRODUCTION

THE concept of standalone microgrids for addressing economic and environment friendly electricity generation is ever pushing the limit of load margin. One of the key objectives in a microgrid is cost effective operation through the integration of large scale renewable energy sources. This factor is also a contributing in voltage instability. In order to address this challenge modern grids often put an effort to introduce the self healing feature through software intelligence. The advent of phasor measurement unit (PMU) has further strengthened the avenue of self healing [1], [2]. Through a framework or multiple layers of decision making processes autonomous systems can be deployed in achieving self healing mechanisms. An end-to-end system configuration often requires a hierarchical structure; The bottom layer for measurement, the mid layer for deploying intelligence in the substation level and finally the top layer is the centralized command [3]. Deployment of an emergency control scheme in the bottom layer can address and solve some of the contingencies in a distributed order avoiding any interventions from SCADA. Such effort helps reducing operational costs and increasing speed of operation; thus local decision making for service restoration is getting more attentions in the recent years [4]–[7]. After a major fault, service restoration in a sectionalized microgrid demands distinct solutions. In [4] a novel self healing approach has been introduced. It distributes the self healing process into multiple segments of a fault affected microgrid. The demand balance is maintained either by adjusting the power output or by shedding loads in each of these sections. However, the study considers that no dynamic and transient stability issues would

arise while applying the self healing process, which often is not the case [8]. System instability in a sectionalized microgrid can be understood by observing the dynamic behaviour of the generators both in pre and post fault conditions [5]. It means in order to develop an automated service restoration mechanism while considering dynamic events, understanding the methods behind low level machine control could be resourceful. [9] argues that analytical calculation of the post fault system instability can give an acute range of post fault operating points. This method is quite effective to simplify the post fault protection schemes but the method does not consider any stochastic element present in the network. Wind power integration, variable demand and fault locations are some of the key elements introducing uncertainties i.e. instability in a multi machine network. As the line voltages and frequency in a microgrid can be controlled by controlling the synchronous machines in the network, the dynamicity in the machine parameters potentially can distinguish different events. Recent literature thus infers that the local or distributed control is quite dependant on the identification of dynamic events under different contingencies [1], [2], [5], [10]. In order to maintain the post fault voltage stability the most common measures are demand response (DR) and involuntary load curtailment (ILC). Under different stochastic scenarios, specially under post fault contingencies while the system is subject to transient and dynamic stability issues, the effectiveness of DR is yet to be discussed in larger contexts [11]. On the other hand ILC is the least desired avenue. Numerous studies, therefore, turn towards the concept of CVC scheme, which is based on controlling active power generation from the fast-response generating units and reactive power generation from VAR sources like synchronous generators [11]–[13]. In [12] the CVC has been formulated as a scenario based multi objective function. Each scenario reflects the availability of wind power and demand. The multiobjective function minimizes the risks of voltage instability at a lower cost. The overall method despite being technically sound lacks analyzing the development of scenario based active and reactive power dispatching scheme from a point of view of a post contingent unstable system. The fast service restoration schemes right after detection of a system instability is therefore not observed in the scenario based assessments which is a key factor in any self healing microgrid. Besides the applied fuzzy satisfying method to select post contingent operating points is not intelligent which also can contribute in delaying the service interruption.

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This study implements a scenario based optimized CVC technique similar to [12] from the perspective of controlling a synchronous machine. Instead of analyzing cost efficiency the methods addresses the transient stability issues in the optimization routine, specially in a system which is vulnerable to critical short circuit faults. In order to address the shortcomings of DR presented in [11] a machine learning based system has been proposed that works on the data prepared by the optimization routine as well as a feature extracted from the machine data. The feature selection process is used to prepare the data set for enhancing the decision making capabilities of the proposed algorithm [14]. The overall objective of the machine learning platform is to identify system instability and based on the stochastic scenario of the wind power and demand, take rapid decisions to stabilize the system when being unstable. The algorithm is trained offline basis and then tested online using IEEE-39 bus **10**-machine systems with an addition of an offshore wind farm at bus-**36** [15].

II. SYSTEM UNDER CONSIDERATION

The proposed micro-grid for this analysis as shown in Figure-2, is an IEEE-39 bus **10**-machine test system. The system is quite suitable for stability analysis [16]. During a critical contingency the system can be divided into a sectionalized network, which is necessary to implement distributed control. To facilitate such distributed control, each area has been equipped with multiple synchronous generators those adopt real power frequency and reactive power voltage droop control. For non dispatchable energy generation a wind power plant based on an induction generator is considered and connected in bus-**36** at the proximity of Generator-7 [15]. The system considers two types of loads; critical invariant and non-critical variable load. The synchronous generators are considered to provide for the base load. The capacity of the wind turbine is chosen to cater the variable load. Based on the availability of the wind power and variable load the loading margin is observed either sufficient or insufficient. The variable load is considered lumped in bus **32** [17]. In order to create different stochastic test scenarios critical short circuit faults have been introduced. The critical fault introduces rotor angle instability as the generators swing against each other in groups [18].

The rotor angle instability introduces large voltage fluctuation in the transmission lines. The proposed CVC eliminates the rotor angle instability by analyzing the dynamic data collected from all the available generators and imposing a distributed supervised secondary control scheme; $\frac{dE_G}{dt} \rightarrow 0$; E_G = Generator terminal voltage. The supervised secondary machine control based on the proposed CVC is a modified and extended approach carried out in [6]. The modification is brought in the data analytics platform by considering system sensitivity in terms of $\partial P_M / \partial V_f$ and $\partial Q_M / \partial V_f$ [19]; where P_M, Q_M are the machine active and reactive power while V_f is the voltage at the fault node. And extension is carried out by introducing **10**-machine system with multiple fault locations. The system is designed to have both normal operating mode and self healing mode. In the normal operating mode the grid

is resilient enough to stabilize the system after the fault is cleared. On the other hand the self healing mode is invoked once a rotor angle instability is observed within an *1-second* window after the clearing of a critical fault. To identify rotor angle instability after the fault a threshold value of rate of change in between -5° to $+5^\circ$ has been chosen. The method is shown in Figure-1 during a short circuit fault near bus-**16** and bus-**17**.

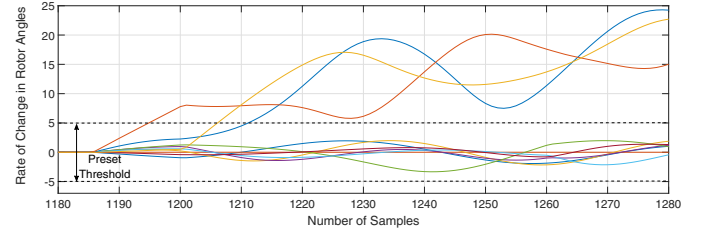


Figure 1. High Fluctuation in Rotor Angle due to a Critical Fault

The post fault contingency is considered as a first swing stability problem which can be damped using a trained linear continuous control (LCC). From each distributed controllers point of view the grid is a single machine infinite bus system; thus, the active and reactive power transmitted through the transmission line can be modelled as $P_i = \frac{V^2 \sin \delta}{(1-k)X}$ and $Q_i = \frac{2V^2}{X} \frac{k}{(1-k)^2} (1 - \cos \delta)$. Here i stands for the synchronous generators, X is the line inductance and $k = \frac{X_c}{X}$; X_c = Series capacitance. Once the proposed algorithm detects an instability it invokes the LCC and damps the oscillation. The LCC is developed based on the proposed CVC optimization technique discussed in details in the later sections.

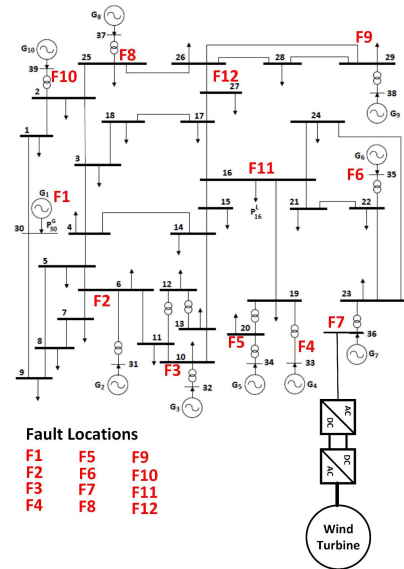


Figure 2. The Micro-grid Model

The model as shown Figure-2 serves the purpose of gen-

erating time series dynamic data in order to train, validate and test the proposed CVC based control scheme. The system uses a primary control based on the so called drooping characteristics of frequency and voltage. The reactive load sharing capacity of a droop controller largely depends on the feeder impedance. By introducing and clearing critical faults overall network topology has been temporarily altered. These contingencies are applied in **Ten** different locations very close to the synchronous generators and **Two** locations in the critical transmission lines that can be disconnected to create segmented grid. The proposed distributed method identifies the most affected generators by any fault and take a relevant action to mitigate it. The algorithm validates the action (decision) by identifying the *1-second* window following the clearanc of the fault. By analyzing this window of machine data in terms of CVC optimization stabilizing actions are categorized and processed. The categorization is prepared based on the post fault transient characteristics of the synchronous machines.

III. PROPOSED SECONDARY CONTROL

In a hierarchical control chain the purpose of the primary control which is to maintain the system frequency and voltage. The primary control in an isolated grid may cause frequency deviation after a critical fault despite maintaining a steady state condition. The secondary control acts on that observed deviation and fine tune the control parameters with a slower dynamics. The slower dynamics decouples the two control schemes. This study implements a centralized secondary control under normal operating mode and proposes a distributed and supervised secondary control during the self healing mode. The secondary control is considered as a part of the hierarchical control scheme of the microgrid [6], [20], [21]. The trigger point to activate the self healing mode is set by creating and observing a stochastic database for the rotor angles and terminal voltages of individual machine.

The secondary control is applied after the machine initialization has been taken care of and the system has reached to steady state condition. The proposed supervised control is a restorative action over the primary controller. This study follows a similar method for the conventional droop characteristics explained elaborately in [1] satisfying the condition $D_{Pi}P_{Ni} = \Delta\omega_{max}$ and $D_{Qi}Q_{Ni} = \Delta E_{max}$. Where, N is the number of distributed energy generators which in this paper is two and P and Q are the generated active and reactive power, $\Delta\omega_{max}$ and ΔE_{max} are the maximum allowed angular frequency and voltage deviations. The dynamic response then can be understood through linearization of the active and reactive power equations to find out their so called small signal models.

$$\Delta P(s) = \frac{G}{s + D_P G} \Delta \omega^*(s) \quad (1)$$

$$\Delta Q(s) = \frac{H}{1 + D_Q H} \Delta E^*(s) \quad (2)$$

Here, the coefficients, G and H depend on the nominal terminal voltage and the rotor angle of the generators and the

transmission line voltages where power is transmitted. The secondary control scheme is evoked if the threshold of the $\Delta d\theta_{max}$ and ΔE_{max} have been crossed after a short circuit fault. Figure-4 shows the model of the secondary control system. The proposed secondary control is based on a distributed machine learning algorithms trained under different stochastic scenarios on a feature augmented data. The workflow for the proposed supervised secondary control is shown in Figure-3.

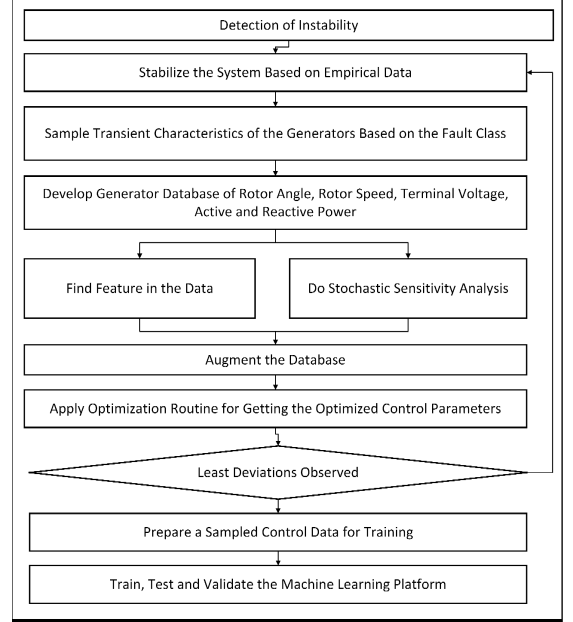


Figure 3. Workflow of The Proposed Method

The data preparation stage is based on sampled stochastic scenarios of random wind power and demand. The wind power is considered proportional to the wind speed. A kmeans clustering technique is used to categorize each stochastic scenario into a cluster. For simplicity this study deploys **9** clusters considering **3** levels in wind speed and **3** levels in demand. The cluster is prepared using a matrix of normalized wind speed and demand data. Figure-5 shows the clusters prepared for simulation optimization.

Based on the different stochastic scenarios and fault locations a sensitivity analysis is also carried out. The sole purpose of introducing a sensitivity analysis is to calibrate the optimization routine. The P-V and Q-V characteristics has been considered under three different contexts pre-fault steady state, post fault transient state and post fault steady state condition in order to estimate the control parameters [19]. One instance of the sensitivity curve is shown in Figure-6;

In Figure-6 four sensitivity curve of the generators { G7, G6, G4, G5 } closer to the short circuit fault is compared to that of a generator { G2 } not affected by the fault. The analysis shows the aperture of the curve increases if the effect of the fault is greater on any machine. The aperture is calculated

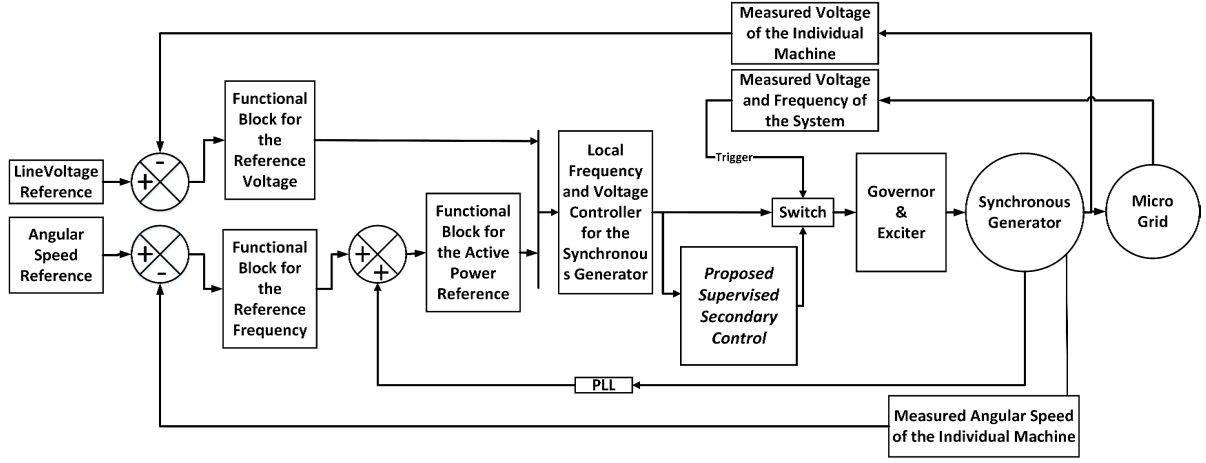


Figure 4. The Proposed Secondary Control Scheme

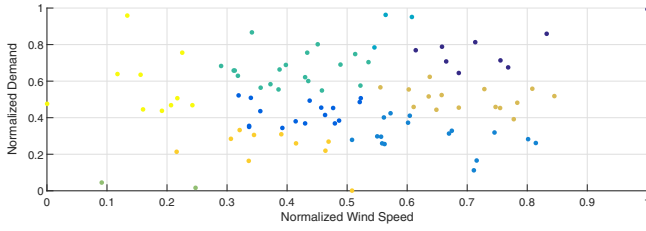


Figure 5. Preparation of the **Nine** Stochastic Clusters

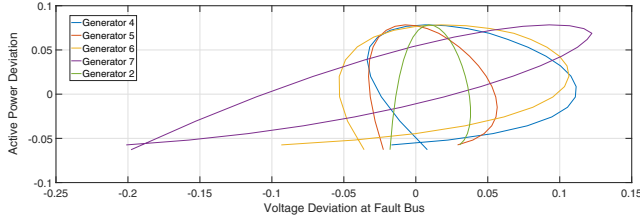


Figure 6. Sensitivity $\partial P_m / \partial V_{fbus}$ Curve of Fault-11

using the numerical integration by trapezoid method. The limit of each response curve is considered between two extreme points over the $\mathbf{X}$ -axis or the ΔV_{fbus} axis. Each curve is then equally distributed into two halves around the extreme point as a convex (Upper) and concave (Lower) perimeters. Finally The overall area is calculated by subtracting the area under the concave curve from the convex; $Area = A_{convex} - A_{concave}$.

$$\int_{V1}^{V2} f(x_{convex}) dx \equiv \frac{V2 - V1}{2N} \sum_{n=1}^N (f(x_n) + f(x_{n+1})) \quad (3)$$

$$\int_{V1}^{V2} f(x_{concave}) dx \equiv \frac{V2 - V1}{2N} \sum_{n=1}^N (f(x_n) + f(x_{n+1})) \quad (4)$$

The calculated area is considered as a feature in the generator data. Each contingency develops a set of feature data of the generators. Under one stochastic scenario the area feature is normalized between the largest and the lowest absolute values. Depending on the feature data the upper bounds of the optimization variables are set while stabilizing the system with a cost function of;

$$Objective : \min(\epsilon_{V_{fault}} = \sum_{i=1}^N [V_{prefault} - V_{postfault}(i)]^2) \quad (5)$$

For the purpose of optimization in the proposed CVC, Genetic Algorithm (GA) has been chosen [22]. GA is optimizing the supervised active and reactive power generation from each generator during the self healing mode for a window of '4-seconds'. The forced power generation is maintained in order to damped the rotor angle instability and the voltage fluctuation. Once the oscillation is damped the supervised secondary control is removed [6]. The objective function is subject to the following constraints;

$$P_{dpfcl} + P_{dpfncl} + P_{Tloss} \leq \sum_{i=1}^{n_g} pg_i + \sum_{i=1}^{n_{ren}} preni \quad (6)$$

Where P_{dpfcl} and P_{dpfncl} are the critical and non-critical loads. Due to sudden change in demands, in some cases deviation in power generation can be observed. In this study the post fault demands are kept constant and any large deviation is neglected. Thus $pg_{i,t} - pg_{i,t0}$ is considered zero for the half an hour span pre-defined for the stochastic data points. Therefore, the upper ramp rate UR_i and lower ramp rate LR_i have been neglected. To maintain post fault frequency stability sufficient spinning reserve should be available. $\sum_{i \in G} SR_{i,t} \geq SSR_t; \forall t \in T$.

Where, $SR_{i,t}$ is the available spinning reserve of individual diesel generator at t -th half hour, and SSR_t is the system wide required spinning reserve. Each generators also follows the generator output constraints, which means the generation does not exceed its upper limit $pg_{i,t} \leq PG_{i,max}; \forall t \in T$ and also for the renewable energy generators $pgren_{i,t} \leq PGren_{i,max}; \forall t \in T$. Furthermore, wind and synchronous generators are subject to their active and reactive power limit $0 \leq P_{scenario_n}^{wind} \leq P_{max,scenario_n}^{wind}$ and $P_{i,min}^G \leq P_i^G \leq P_{i,max}^G$; $0 \geq Q_{scenario_n}^{wind} \geq Q_{min,scenario_n}^{wind}$ and $Q_{i,min}^G \leq Q_i^G \leq Q_{i,max}^G$.

After each optimization routine is completed a stability database of stochastic wind and demand data with different fault location is prepared. The data table contains the information of forced active and reactive power generation from each generator during each contingent scenario. Once the data table is prepared an *Adaptive Neuro Fuzzy Inference System* is trained 'offline', as shown in Figure-7. The fuzzy inference system is considered as having dual inputs 'x' and 'y' that result in an output of 'z'. For a first order Sugeno fuzzy model a typical if-then rules can be established as the following;

Rule 1: If $x_1 = a_1$ and $x_2 = b_1$ then output $z_1 = p_1 \times x_1 + q_1 \times x_2 + r_1$

Rule 2: If $x_1 = a_2$ and $x_2 = b_2$ then output $z_2 = p_2 \times x_1 + q_2 \times x_2 + r_2$ The terms p_i , q_i and r_i are the linear parameters of the consequent 'THEN' part of the first order fuzzy inferencing model [23].

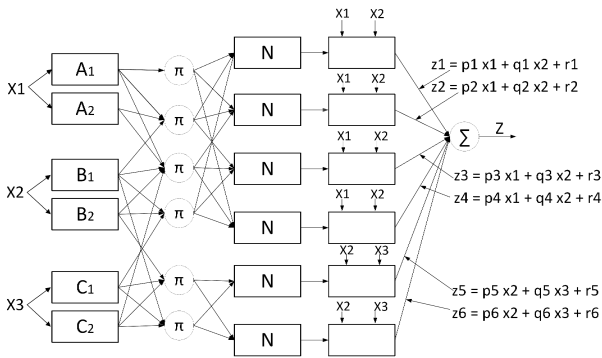


Figure 7. Five-layer Three-input Four-Rule fuzzy model (Sugeno) [23]

The outcome of the proposed algorithm finally can be stated as optimized supervised active and reactive power output from the affected generators in a fault stricken segment of a microgrid.

IV. RESULT ANALYSIS

The data preparation step develops a table based on the stochastic scenarios of wind speed and demand. The Table-I shows some of the distributed control incidents for the Generator-7 and Generator-9.

The scenario based data consists of the stochastic cluster, fault location and sensitivity feature is fed to the ANFIS model in order to predict the optimized active and reactive power

Table I
STOCHASTIC DATA PREPARATION STAGE FOR GENERATOR-7&9
(SELECTED SCENARIOS)

Wind Power	Demand	Cluster	Fault Location	Sensitivity Feature	Optimized Active Power (P.U.)	Optimized Re-Active Power (P.U.)
High	Med	2	B-16	0.4712	G7: 0.70	G7: 0.62
Low	Med	8	B-16	0.4034	G7: 0.75	G7: 0.56
Med	Low	4	B-26	0.1729	G7: 0.45	G7: 0.57
—	—	—	—	—	—	—
High	Med	2	B-16	0.2052	G9: 0.41	G9: 0.62
Low	Med	8	B-16	0.2284	G9: 0.39	G9: 0.62
Med	Low	4	B-26	0.5913	G9: 0.73	G9: 0.55

generation from each generator in a distributed order. One incident of ANFIS based prediction for the Generator-7 is shown in Figure-8.

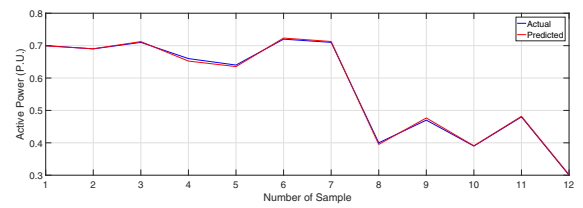


Figure 8. ANFIS Based Prediction for Generator-7

The result for predicting the optimized power for Generator-7 is quite accurate. However, a minor classification error is observed in the data sample 4. From an individual machine perspective such a minor classification error can be neglected. However, a larger classification error will lead the system to further instability.

The overall performance of the proposed method is shown in Figure-9 during a critical fault introduced in the Bus-16. The critical fault is cleared by disconnecting the transmission line between the Bus-16 and the Bus-17, as well as the Bus-16 and the Bus-15. Due to the process of clearing the fault two segments are created. The *Segment-1* consists of the synchronous machines G4, G5, G6, G7; while the *Segment-2* has the rest of the machines connected. The contingency introduces rotor angle instability in the *Segment-1* thus supervised control is imposed on the 4 mostly affected synchronous machines.

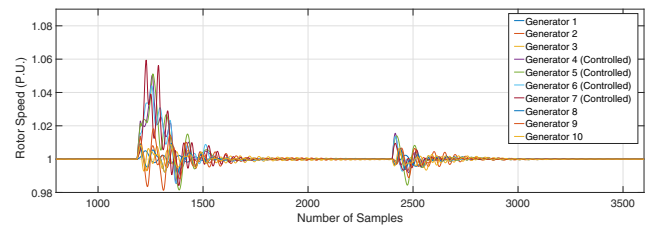


Figure 9. Stabilizing the Segmented Microgrid with the Proposed Algorithm

Furthermore in Figure-10 the rotor angle deviation compare to the system slack bus and rotor speed of the Generator-

7 are elaborately presented. The solid *red* line marks the beginning of the short circuit fault; the dashed *red* line marks the clearance of the fault. The solid *blue* line marks the identification of rotor angle instability and starting of the supervised control scheme while the dashed *blue* line marks the end of the supervised control scheme and handing over to the primary control of the system. The solid *green* line marks the re-closing of the transmission line between Bus-15, Bus-16 and Bus-17.

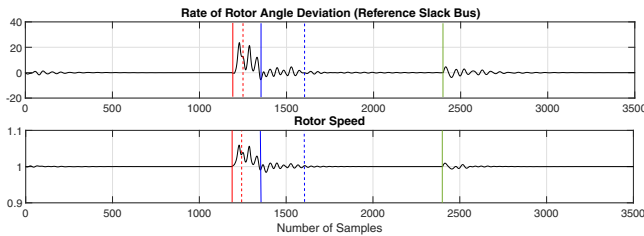


Figure 10. Generator-7 Data

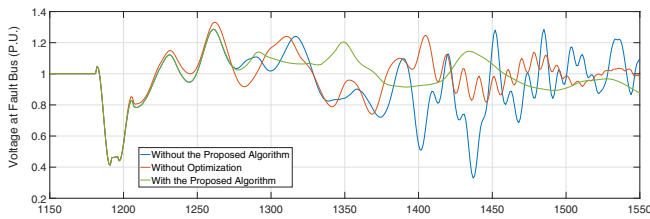


Figure 11. Comparison of Voltages at the Fault Bus With Different Methods

Finally, in Figure-11 a comparison between the fault bus voltages is shown. The comparison is carried out among the proposed algorithm with optimized CVC, without the CVC optimization (prefault fixed value of the control parameters) and without the proposed algorithm. It is observed that the proposed algorithm has better damping coefficient thus better resiliency than the rests.

V. CONCLUSION

The proposed algorithm successfully eliminates rotor angle instability and restores system voltage in a segmented microgrid. The method works in a distributed platform without any intervention from the central station during a post fault operation. However, the algorithm is tested on a sampled post fault scenarios with only 9 clusters. A comprehensive analysis with more variations would provide further insight. The study also does not consider classification errors. Thus the full ramification of number of clusters against accuracy is not addressed in this study. Beside these minor issues, the overall performance of the algorithm on IEEE-39 bus test system for the purpose of self healing is promising.

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