A Machine Learning based Optimization for Post Fault Restoring a Stand-alone Microgrid- A case study of Baglung Microgrid

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Abstract
The rapidly increasing penetration of renewable energies has introduced severe challenges to power system voltage controls due to the highly intermittent and uncertain power output of renewable energies. If a short-circuit fault occurs in a microgrid while operating at its design limit, often cost-effective system recovery becomes a challenging task. In such situations, predictive analytics can be used to enhance system recovery programs. The training MG network consists of one major hydroelectric plant and an intermittent and variable solar plant without an energy-storing device battery. The main overall loads are divided into two sections named critical non-controllable base load and non-critical controllable load. The microgrid (MG) is modelled in such a way that loads are lumped into a single point and energy storage devices are not taken for capturing both the directional power flow pattern in the MG and also the starting ramp-up time for the standby diesel generator, which is considered very small. The training network has one hydro turbine-based synchronous generator, two backup diesel generators (synchronous) of G1 = 200 KVA and G2 = 300 KVA, and a voltage source converter-based solar power plant of 500 KW. Total demand is higher than the total capacity of synchronous generators as power plants with an 800 KW controllable load and a 250 KW critical load. In each severe case, four different types of faults are considered: L-G, L-L, LL-G, and LLL-G near the major generating plant. Each type of fault is considered for various combinations with solar power and controllable non-critical load by 5000 different cases to get overall 20000 training data. The fault is taken at a simulation time of 15 seconds and cleared at a later time. A restoration plan is scheduled by starting up DG and/or load curtailment. In this thesis study, four types of faults are considered and analyzed to develop a cost-effective system recovery scheme in a stand-alone microgrid. After analyzing different cases with each type of fault in the training network and plotting the box plot for MG voltage with four different faults, the most severe fault was "LLL-G" observed. For the Training Classification Learning tool in MATLAB, the MathWorks-approved simplified MG model is considered for simplicity and runs over a very large number for data collection with calculating during fault and post-fault voltage, as well as the needs of one or both diesel generators and/or shedding individual or both loads to get secondary restoration in a stand-alone microgrid. The collection of possibilities of instability (POS) for each cluster with 100 numbers is classified and termed one of the predictors in the classification tool. The collected 20,000 sets of data are considered for training different models of classifiers available in the MATLAB toolbox. Out of all these data, there are 1502 data points (7.51%) with mostly L-G faults having less than 5% POS so that they remain in stable condition, and the remaining 18498 data points have >5% POS and require restoration action, and only these data points are trained in classifiers to get the required restoration action. The classification of restoration action has 15 different responses with a secondary restoration plan and also has five predictors: solar power, controllable load, POS, type of faults, and during a fault, microgrid voltage. Seven different classifications are modelled without enabling principal component analysis (PCA) and have 20% for ross-validation. Among them, the highest accuracy with 93.20% and area under curve (AUC) for ROC with 0.98 are obtained for the bagged tree type of classifier available in the MATLAB Machine Learning App. Based on this bagged tree-assemble model, it is selected for the best results in a system restoration plan in a stand-alone microgrid. After the completion of a well-trained bagged tree classifier with a training network, this model is tested on a 3-bus computational practical stand-alone model for Baglung microgrid. In this 3-bus network, a larger generating unit with 26 KW is considered a slack bus, and other buses are termed PQ load buses. Before any fault, the system is in a healthy steady-state condition, with the voltage in each bus within the limit. Controllable non-critical load is assumed to be 60% of peak total demand in the network. A deadly 3-phase LLL-G short-circuit fault was placed near the major generating unit and just cleared after that. During a fault or outage of a major generating unit condition, based on this basic input data, the bagged tree classifier gives output to have "DG1" start output so that it remains in stable condition. The capacity of DG by economic dispatch is calculated using the GA algorithm within renewable power plant capability and bus voltage limits. The following results were obtained: Dg optimal size = 16.2.1 KW (~20 KVA) at BUS-1, TL Loss = 1.857 KW, Total Active Load = 58.4 KW, Total Reactive Load = 43.7 KVAr for the best cost-effective restoration plan for stand-alone Baglung microgrid.

Keywords: *Distributed Generation, Genetic Algorithm (GA) Machine Learning, MATLAB, Microgrid (MG), power network, possibility of instability (POS), renewable power sources, service restoration (SR)*

I. INTRODUCTION

Micro hydropower plants have been very successful in rural electrification in Nepal compared to many countries around the world. Electrification in rural areas through grid maintenance seems particularly unfeasible in the country due to high diffusion/decentralization costs, low per-household consumption, and few buyers. On the other hand, local resources/streams are abundant. These are the reasons that justify the recognition of MHP. Renewable energy could meet nearly 80% of global energy demand within four decades and reduce global dependence on fossil fuels [1]. Renewable energy sources will also bring environmental benefits such as reducing pollution, restoring soil and slowing global warming. The development of renewable energy technology will boost the global economy and also bring more job opportunities. Energy is one of the important human needs. The fundamentals of global economic stability and growth are safe, reliable and affordable energy. Global economic growth depends on global supply, and oil accounts for about 40% of global energy consumption and most transportation fuels [2]. In modern microgrids, the integration of distributed generators (DGs) forces a more localized and decentralized approach [3-8]. This leads to long preparations, often making major errors, or even service interruptions. Therefore, an alternative approach would include the construction of short-term forecasting systems for non-dispatchable energy resources [9]. One of the most researched methods in this field is the application of machine learning algorithms [10-11]. However, most studies are limited to analyzing algorithm accuracy by comparing actual and predicted data. Therefore, very little research has been conducted to predict power system security to implement service recovery (SR) measures [12-14]. On the other hand, significant efforts have been made to improve SR plans by implementing advanced measurement infrastructure (AMI), multi-agent systems (MAS), information-based architecture, progressive coverage (PH), linear calculation, etc. [15-17]. These models are computationally complex and often ill-suited to the timescale of the suspected fault, including variables of such integer resolution that they constitute a double signature of violation of the angular constraint rotor. This problem can be solved by considering two types of uncertainties, which are severe errors in the vulnerable and non-vulnerable periods. These phases can then be decomposed into multiple stochastic programs based on several scenarios [18].

The rest of the paper is included as follows: Section 2 explains design and analysis of a standalone solar PV system, Hydro-generator and suitable number of DGs as stand by unit with microgrid. Section 3 explains about the methodology used in this thesis. Section 4 introduces the overall result and graph of training IEEE model simplified stand-alone microgrid and testing in the actual Baglung computational model microgrid. Section 5 discusses the conclusions of this research.

II. THE MICRO-GRID TRAINING MODEL

Two different independent microgrid models were used in this thesis to study cost-effective system restoration and power dispatching of generating units. To create different machine learning (ML) based system retrieval training programs, a small-scale system is used, as shown in Figure 1. To understand and analyze the impact of the proposed method with AI-based system stability index predicts over a larger scale. network, isolated mode operation of the Baglung microgrid is used.

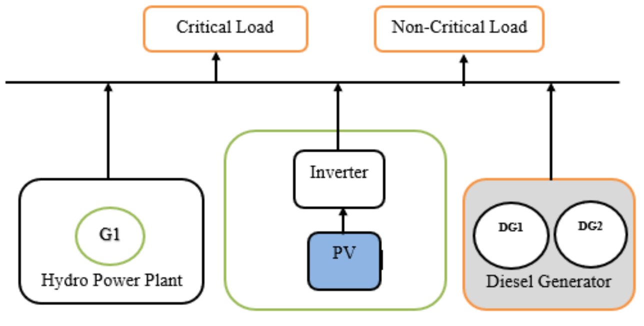

Figure 1: Test Network for Algorithm Development [2][7]

The smaller network includes a hydro turbine-based synchronous generator, two emergency diesel generators (synchronous) G1=200 KVA and G2=300 KVA and an inverter-based solar power plant voltage 500 KW. Loads are grouped together on a common transmission network. This distributed approach is inspired by microgrids. However, this model differs in dividing the charge into two parts; Critical and non-critical loads. The total demand is greater than the total capacity of synchronous generators such as power plants. Suppose the training network has a controllable load of 800 KW and a critical load of 250 KW.

2.1 Solar energy model

Iso-tech 215 W array, at 25°C and specified irradiance, series=23, parallel=100 array are used for modeling 500 KW solar panel. The total system is designed and executed in MATLAB/SIMULINK environment.
The Simulink library has all the essential electronic components to show any electronic circuits. A boost converter has made utilizing a capacitor, an inductor, a diode and a switch that appears in figure 2.

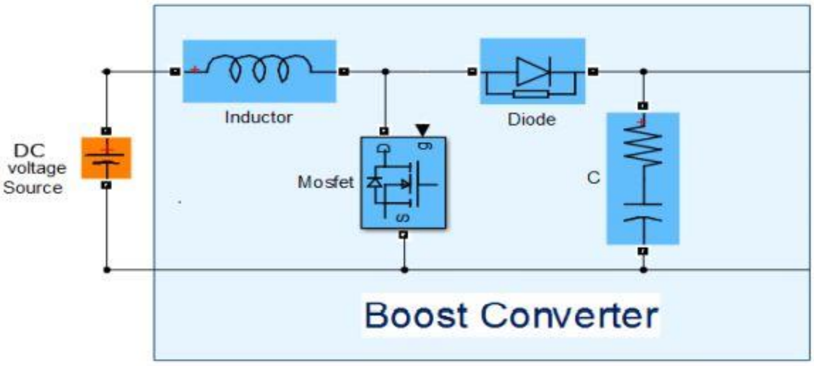

Figure 2: Circuit diagram of a DC-DC boost converter

$$L_{Boost} = \frac{V_{input}(V_{output} - V_{input})}{V_{output} * \Delta I * f_{sw}} = 2.92 \text{ mH}$$

$$C_{Boost} = \frac{I_{output}(V_{output} - V_{input})}{V_{output} * \Delta V * f_{sw}} = 3240 \text{ µF}$$

The problem considered by MPPT methods is to automatically find the voltage VMPP or current IMPP at which a PV array delivers maximum power under a given temperature and irradiance. In P&O method, the MPPT algorithm is based on the calculation of the PV output power and the power change by sampling both the PV Array current and voltage. The overall flow diagram is shown in figure 3. Each curve has its maximum power point. It is at this point, where the corresponding maximum voltage is supplied to the converter.

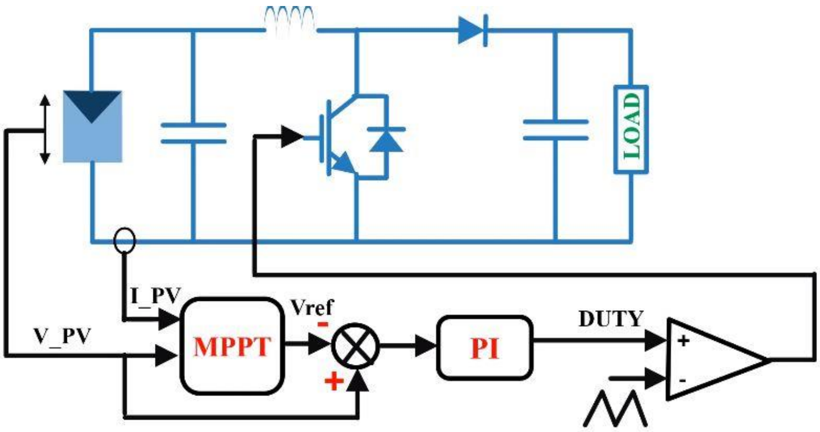

Figure3: Control diagram of PV with P&O MPPT

For supplying power to the AC loads, we have incorporated a DC to AC converter (inverter) into our microgrid system. Design LCL filter for solar inverter:
Rated Power (S) = 500kva

Rated Frequency (f) = 50 Hz

Output L-L Voltage (V_{abc}) = 400 V (V_{rms})

Switching Frequency of inverter (F_{sw}) = 10 khz

Resonant Frequency (F_{res}) $= \frac{1}{10} * F_{sw} = 1$ khz

a) Finding value of Capacitance

Reactive power requires = 5% of rated power

$C_f = \frac{0.05*S}{V^2*2*pi*f} = 500$ µF

b) Finding value of inductor

V_L (max)= 20% V_{abc}

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$L_1 = L_2 = \frac{0.2 * V_{grid}}{2\pi f * I_g} = 1mH$

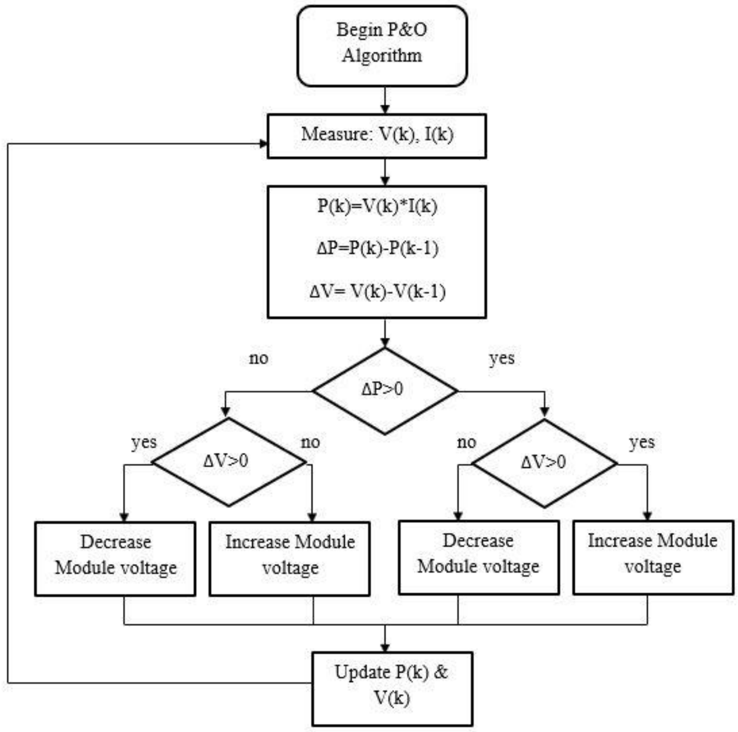

Figure 4: Flowchart of P&O MPPT technique

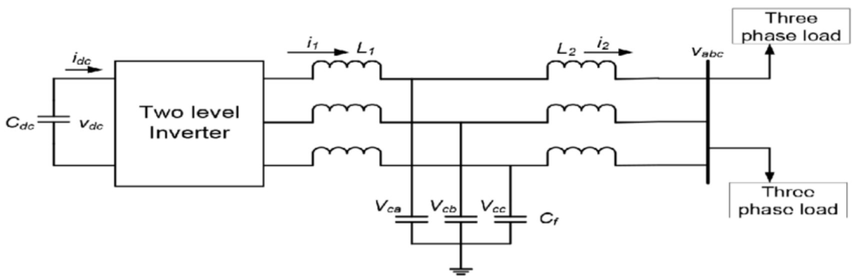

Figure 5: Three phase solar Inverter with LCL filter

2.2 Hydro Plant model

Some important governing equations to model the micro hydro power plants are given by Equation 1 and 2. which represents the flow rate and the developed mechanical power at the shaft respectively in terms gate opening of the system and the net head.

$$Q = G*H \quad (1)$$

Where Q is flow rate in m^3/s, G is gate opening in rad, H is net head in meter. The developed power, Pm in turbine can be written as

$$P_m = A_t H (Q - Q_{nl}) \quad (2)$$

where, A_t is the turbine gain, $A_t = \frac{1}{g_{FL} - g_{NL}}$. Q_{nl} is the no load flow rate, g_{NL} and g_{FL} are the full load and no-load gate opening in p.u.

four signals, stator voltage V_q (pu), stator voltage V_d (pu), rotor speed We pu), and output active power P_e (pu) are demultiplexed. Signals like rotor speed We, and output active power Pe are used as feedback signals to the hydro turbine governor block to complete the close loop path, and rest two signals like stator voltages V_q and V_d in per unit are fed back to the block of excitation system. The rating of micro hydro generator is considered to be 1000KVA, 50Hz and 400V.

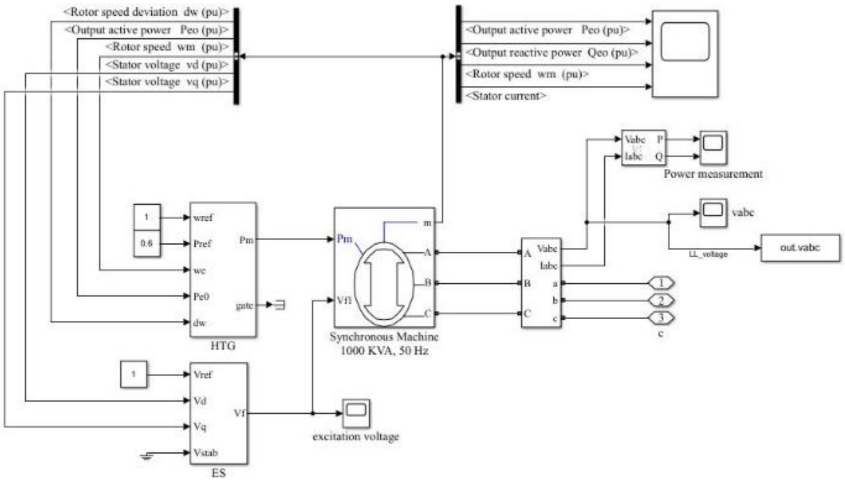

Figure 7: Model of Hydro power plant 1000 KW

2.3 Load model

$$P_{Load} = P_{CL} + P_{NCL} \tag{3}$$

where P_{CL} is the base critical load and P_{NCL} is the non-critical controllable load. The models are then used to generate random data points for a Monte Carlo simulation.

2.4 Diesel Generator model

The main parts of this model are the diesel engine and the three-phase synchronous generator. The diesel engine consists of an IC engine and its governor. Using a PID controller and actuator, the diesel engine's governor maintains a constant operating speed.

2.5 Security index probability of instability

Due to the possibilities of having numerous post disturbance initial conditions, generalizing service restoration plans is quite a challenge. This study thus, assumes that the post fault initial conditions only differ from the pre-fault operational conditions only in the topological layer as a bus isolation at the affected segment. For further simplification, the startup time of the backup diesel generators are considered negligible. A Monte Carlo simulation-based approach is taken to prepare the POS database. The POS database indicates which cluster has the probability of being unstable after a critical fault. The first two columns represent generation from solar and non-critical loads right before the three-phase fault takes place. Clusters are used in training the machine learning platform as:

$$Lowest: \sum_{i=1}^{3}(Centroid_{ki} - Datacolumn_i) \tag{4}$$

Here, $Centroid_{ki}$ represents i^{th} |i ∈ {1, 2, 3} centroid for the k^{th} cluster.

The POS is calculated as;

$$POS_k = \frac{\sum_{i=1}^{N_k} S_{ik}}{N_k} \tag{5}$$

Here, k is the current data cluster, N_k is the total number of simulations in each cluster. S_{ik} is 1 if the system becomes unstable and 0 if the system remains stable.

2.6 Data for Fault Analysis

The proposed microgrid considers four instances of the line voltage; pre-fault line voltage V_{pre}, during fault line voltage V_{flt}, line voltage during the post fault restoration V_{rst}, line voltage after the post fault restoration V_{post}. The aim of this study is to accurately predict system operation strategies that will lead towards achieving a stable and optimal post fault line voltage. The transition period from the fault state towards the restoration state has been considered similar for all the operational strategies. Incidents such as starting up of a backup generator is considered under the conditions when energy balance cannot be made.

$$\sum_{i=1}^{n_g} Pg_i + \sum_{i=1}^{n_{ren}} Pren_i < P_{dpfcl} + P_{dpfncl} + P_{Tloss} \tag{6}$$

Where, P_{dpfcl} is post fault critical load, P_{dpfncl} is the post fault non-critical load, P_{Tloss} is the transmission line loss, p_{reni} power generated from the renewable energy sources, n_g is number of hydro generators, n_{ren} is the number of renewable energy sources.

The diesel generators are presented as to the swing equation model where the capacities are subject to;

$$P_{gimin} \leq P_{gi} \leq P_{gimax} \tag{7}$$

$$Q_{gimin} \leq Q_{gi} \leq Q_{gimax} \tag{8}$$

$$0 \leq P_{li} \leq P_{di} \tag{9}$$

$$0 \leq Q_{li} \leq Q_{di} \tag{10}$$

$$V_{timin} \leq V_{timax} \tag{11}$$

Here, P_{li} and Q_{li} are the load after restoring the system, P_{di} and Q_{di} are the actual active and reactive demands, V_t is the voltage on the generator. Therefore, the overall load shedding according to each of the sixteen actions is $(P_{di} - P_{li})$.

2.7 Preparation For Classification

During the development phase of this study, 16 possible classes were selected for the algorithm. Each layer represents a post-fault decision indicating the energy distribution scheme. These types are only relevant if a severe three-phase fault occurs. The POS database provides an indication of instability based on solar and non-critical loads measured at the time. These three cases data are compared with cluster centroids for labeling. If the probability of instability is greater than 5% for the identified cluster, then the cluster is considered a potential candidate for the proposed optimized recovery method. For other events, this method is ignored. Sixteen categories or decisions are identified in Table 1.

Table 1: Sixteen probable restoration schedules

Decision	Start Diesel-1	Start Diesel-2	Shed Load-1	Shed Load-2
1	0	0	0	0
2	0	0	0	1
3	0	0	1	0
..	..	..	..	..
..	..	..	..	..
15	1	1	1	0
16	1	1	1	1

A disaster recovery diagram performs one of these sixteen actions. The main objective of every decision is to maintain as small a gap as possible between the pre-fault and post-fault voltage states. The goal is achieved by implementing a comprehensive search-based optimization technique. The appropriate function chosen will minimize the sum of squared differences between the line voltage before and after the fault.

$$Objective: min\left(\sum_{i=1}^{N}\left[V_{prefault} - V_{postfault}(i)\right]^2\right) \tag{12}$$

Where i is the data point in consideration. N is the total number of data points considered once the fault is cleared. $V_{prefault}$ is the stable line voltage before the fault and $V_{postfault}$ is the post fault stable line voltage.

2.8 Process for economic dispatch

The final step of the proposed approach addresses the secondary objective of this study, which is post-redundancy economic coordination (ED). The objective function assumes that the aforementioned classification and validation are correct and thus the predictions can be used to manipulate the constraint boundaries. The cost function for the ED problem is to minimize the total operating cost of the microgrid after resolving the problem and stabilizing the system. This objective is achieved by optimizing diesel generator production and/or optimizing non-critical load shedding. The cost is calculated using different quadratic functions for the generators.

$$Objective: Min\left(\sum_{Dg1} C_i\left(P_{dg1}\right) * \sum_{i=1,2,3}(Vpost - Vfault)^{\wedge}2\right) \tag{13}$$

Subjected to:

$$P_{Load} + P_{Tloss} \leq \sum_{i=1}^{n_{ren}} Pren_i + P_{Load\_Schedding} + P_{dg} \tag{14}$$

$$Pgren_i \leq PGren_{i,max} \text{ [26,24,12]} \tag{15}$$

$$0.95 < V_{post} < 1.05 \tag{16}$$

$$I_{12} < 10 \text{ A} \tag{17}$$

$$I_{23} < 10 \text{ A} \tag{18}$$

$$C_i = 1 \tag{19}$$

Where, $C_i(P_{gi})$ is the cost function of the i[th] generator and (P_{di}) for the cost of shedding load. The inequality constraint considers that the total demand and line losses have to be either equal or less than total generation from the renewable sources preni and the diesel generators Pgi after shedding loads if required. The load shedding is represented as PLi. Each generator also follows the generator output constraints, which means the generation does not exceed its upper limit.

The ED is then solved using genetic algorithm (GA). Here the GA applies five standard steps: population initialization, evaluation, selection, crossover and mutation.

III. METHODOLOGY

The proposed method determines this criticality and prepares a set of optimized backup scenarios to restore the system. The machine learning-based algorithm leverages an optimization platform to achieve the lowest possible operating costs after ensuring voltage quality across the entire network in the event of a power outage. The goal is achieved by implementing a set of encapsulated decision tree-based systems to perform forecasting, followed by a genetic algorithm (GA) for service recovery. Many previous studies have successfully implemented security and reliability metrics for system analysis. This study takes a similar approach to measuring system security by introducing a binary security metric called Probability of Stability (POS). This index considers several short-circuit fault situations that result in isolation of the generator bus in the affected area. The POS database is prepared using the Monte Carlo simulation method. The stability analysis performed in this study has a hierarchical structure with the primary objective being recovery and the secondary objective being economic distribution. Optimization is discussed in terms of system stability with the lowest possible operating costs.

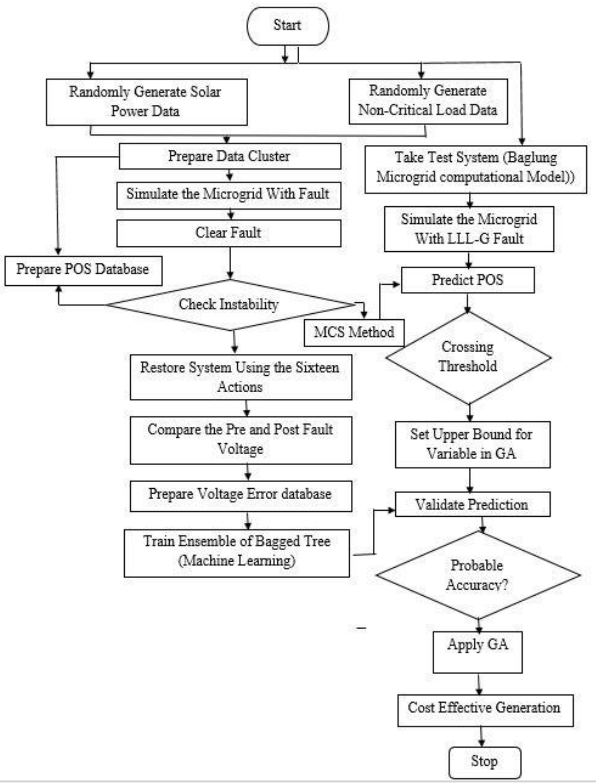

Figure 8: Work-flow of the proposed algorithm

IV. RESULT AND DISCUSSION

4.1 Data Model

To build the forecasting system, three data models on solar energy and non-critical loads were prepared. N number of random data points are generated using these models. Monte Carlo-based simulation is then used with the data points to develop a Probability of Stability (POS) table. Each scenario has a three-phase fault.

4.2 Training MG Network with faults

The training MG network consist of one major Hydro power plant with intermittent and variable solar plant without energy storing device battery. The Main overall loads divided into two section named as critical non-controllable base load and non-critical controllable load. Four different types of faults as L-G, L-L, LL-G and LLL-G are consider near the major generating plant in each severe case. Each type of fault is considered for various combination with solar power and controllable non-critical load by 5000 different cases to get overall 20000 training data. Fault is taken at simulation time of 15 sec and cleared at less time and schedule restoration plan by starting back up DG and/or load curtailment. Figure 9 and Figure 10 shows the microgrid voltage and microgrid frequency respectively for 314.5 KW solar power, 510.82 KW controllable load and LLL-G fault is considered at near major genrating hydro plant. During Fault microgrid voltage as 0.28 p.u. and microgrid frequency 0.985(min) are monitored. After fault clearance and DG1 start and Shed Load1 action need to perform for system restoration and after fault microgrid voltage maintained at 0.99 p.u.

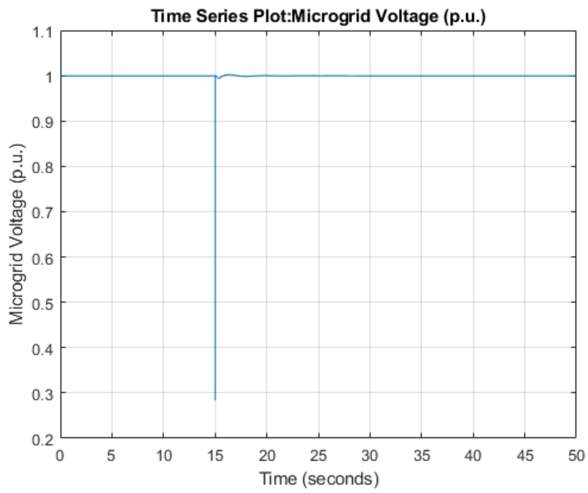

Figure 9: Time Series plot for Microgrid Voltage for LLL-G Fault

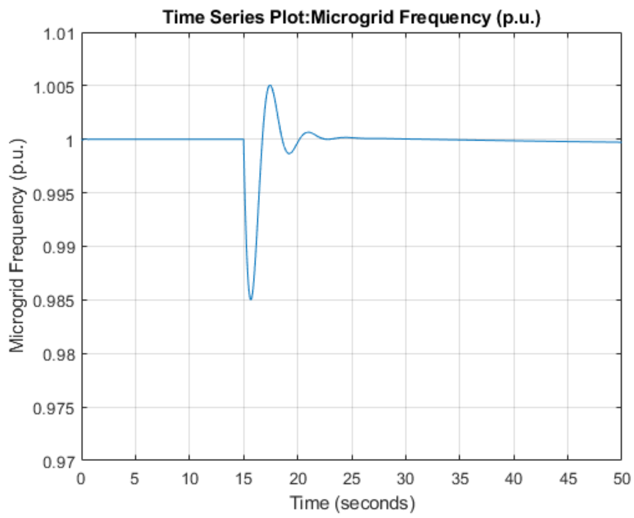

Figure 10: Time Series plot for Microgrid frequency for LLL-G Fault

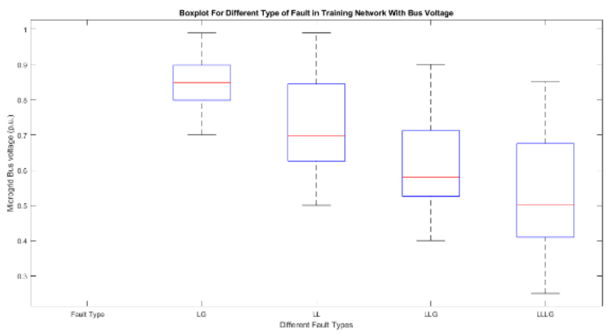

Figure 11: Box Plot for different Fault in test network

Based on Training model network large number of data it is concluded that among the given faults, LLLG or 3 phase faults are most severe. LG or line to ground fault is least severe. Line to line fault is more severe than line to ground fault while double line to ground fault is one level severe than LL. The order of Severity of faults is given below:

LLLG>LLG>LL>LG

4.3 Training classification learning App

For Training Classification Learning tool in MATLAB, MathWorks approved simplified MG model is considered for simplicity and run over very large number for data collection with calculating during fault and post fault voltage, also staring needs of one or both diesel generator and/or shedding individual or both loads to get secondary restoration in stand-alone microgrid. The collection of possibility of instability (POS) for each cluster with 100 numbers are classified and termed as one of predicters in classification tool.

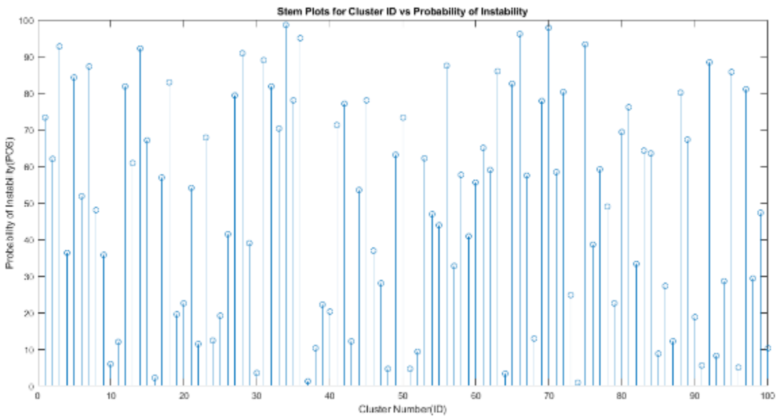

Figure 12: Stem plot for 100 sets POS

4.3.1 Training data sets

Collected 20000 sets of data are considered for training different model of classifier available in MATLAB toolbox. Out of these all data, there are 1502 data (7.51%) with mostly L-G fault have less than 5% POS so that they are remained as stable condition and remaining 18498 data have >5% POS and they require restoration action and only these data are trained in classifier to get required restoration action.

So, there is always high risk of instability of short circuit fault near major generating unit operated in stand-alone microgrid. For effective, reliable and efficient with clearance of major short circuit fault near generating bus, any restoration scheme is required to recover system to its initial healthy condition and in this thesis secondary restoration plan are examined by means of either controllable load curtailment and/or starting of standby sets of diesel generators.

Table 2: Training network data for restoration action 5/20000

S.N.	Solar Power (KW)	Controllable Load (KW)	Cluster ID	POS(k)	Fault Type	During Fault Volt	Post Fault Volt
1	440.92	799.93	59	68.7	LLG	0.48	0.96
2	465.55	689.98	69	82.8	LLG	0.55	1.04
3	218.84	556.76	53	74.6	LLG	0.42	0.99
4	362.21	589.21	63	54.6	LL	0.52	0.97
5	134.58	132.47	74	73.8	LL	0.48	0.99

4.3.2 Classification Output

The classification of restoration action has 15 different responses with secondary restoration plan and also have five predictors and they are solar power, controllable load, POS, Type of Faults, and During fault microgrid voltage. Classification is modeled without enabling Principal component Analysis (PCA) and have 20% for cross validation. The following accuracy and AUC are obtained for each type of classifier available in MATLAB Machine Learning App. Based on these Bagged Tree-Ensemble model is selected for best results in system restoration plan in stand-alone microgrid.

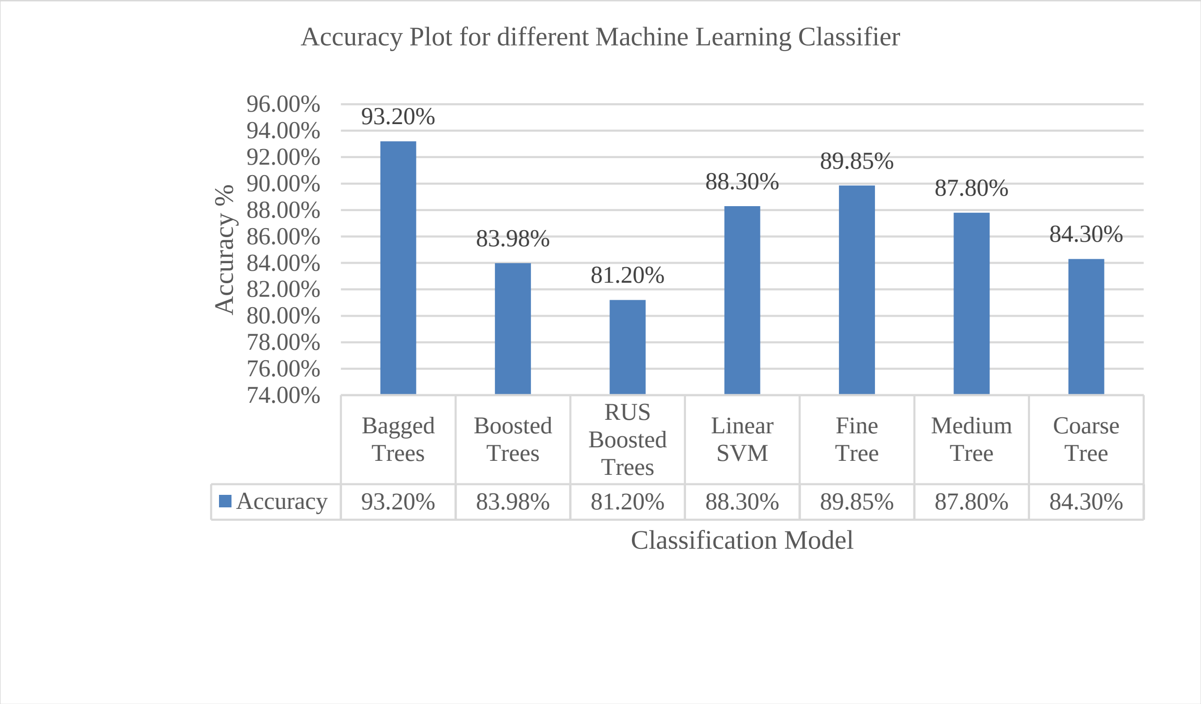

Figure 13: Accuracy Plot for different Machine Learning Classifier

Table 3: Results for different Training Classifier in Machine Learning

S.N.	Model No.	Classification Type	Class	Accuracy	AUC of ROC
1	1.1	Bagged Trees	Ensemble	93.20%	0.98
2	1.2	Boosted Trees	Ensemble	83.98%	0.93
3	1.3	RUS Boosted Trees	Ensemble	81.20%	0.98
4	2.1	Linear SVM	SVM	88.30%	0.98
5	3.1	Fine Tree	Tree	89.85%	0.97
6	3.2	Medium Tree	Tree	87.80%	0.98
7	3.3	Coarse Tree	Tree	84.30%	0.98

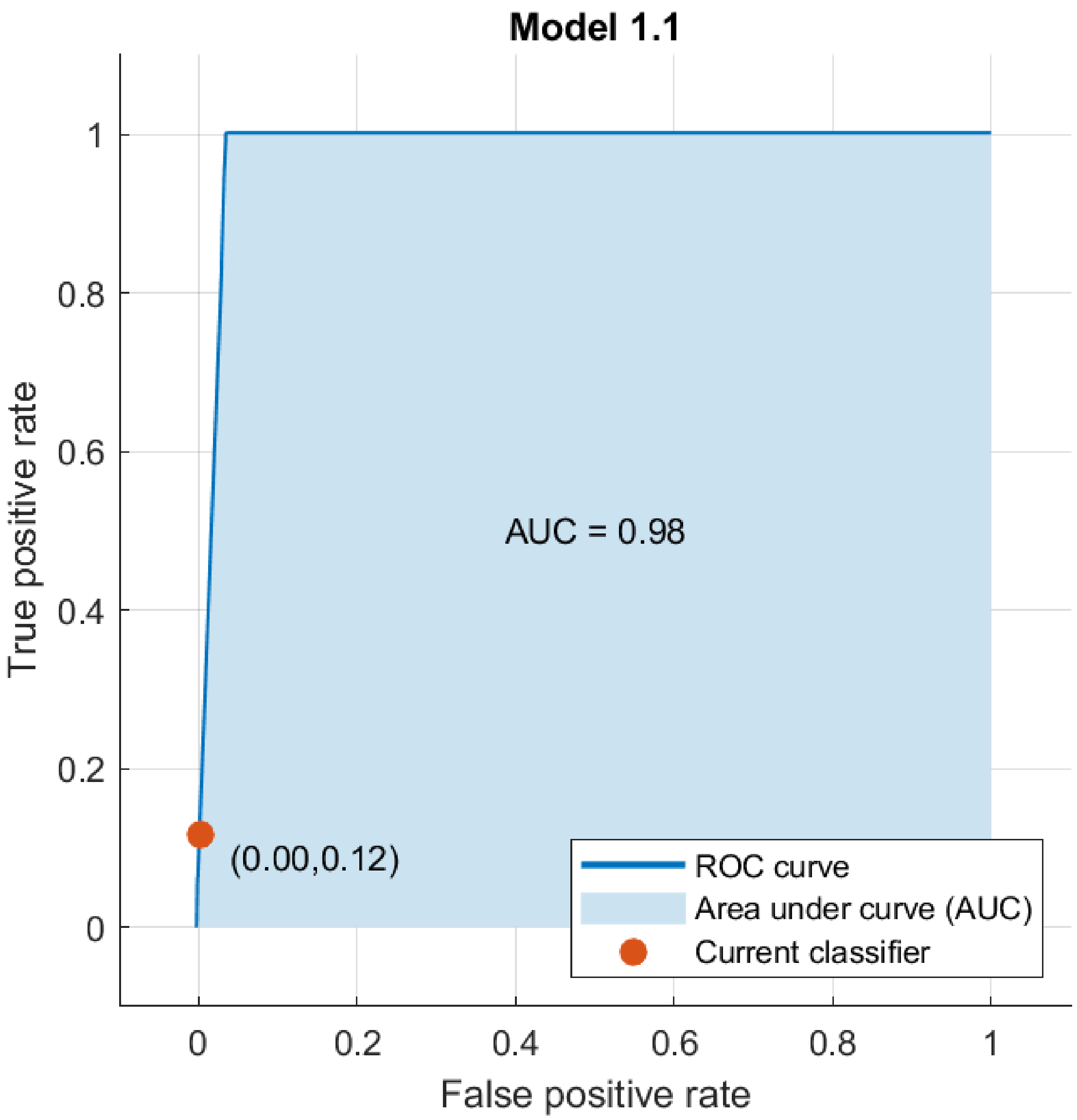

Figure 14: ROC Curve for Bagged Tree Classifier

4.4 Testing on Baglung Computational Model Microgrid

According with the data's, assume base KV=0.4, Base KVA=100 KW and load and generating unit has approximately 0.8 p.f. lagging power factor. In this 3-bus network, larger generating unit with 26 KW consider as slack bus and other bus are termed as PQ load bus. Primarily ELC and AVR in microgrid served as frequency control and voltage control respectively and before fault system is in healthy steady state condition with voltage in each bus are within limit. Controllable load is assumed 60% of peak total demand in Network.

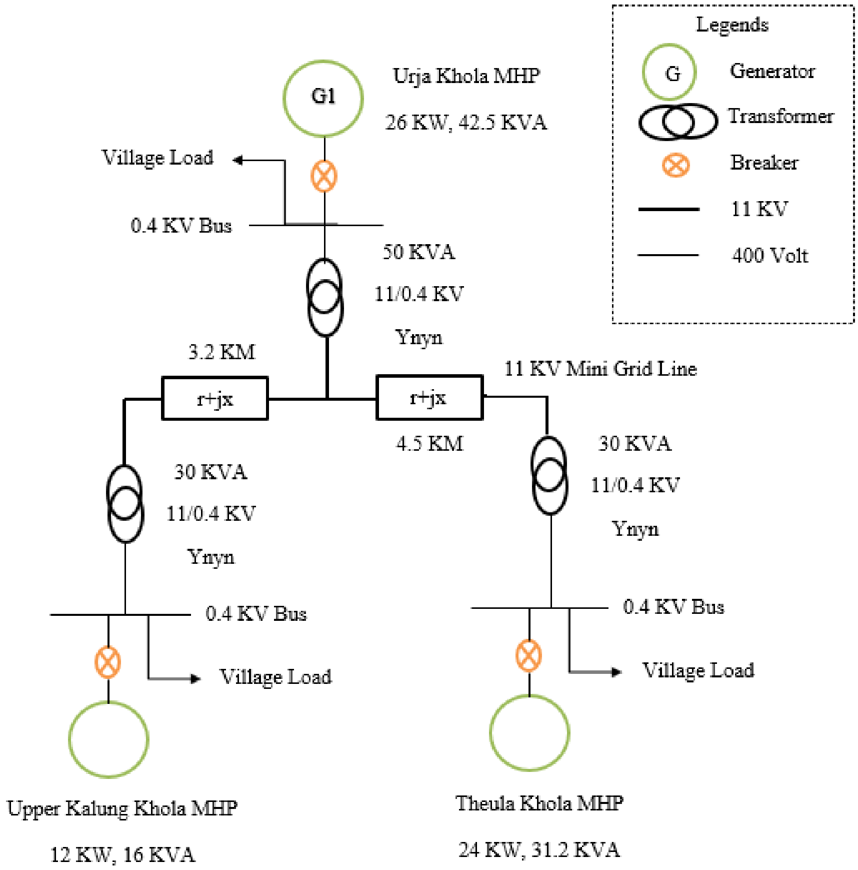

Figure 15: Baglung Microgrid computational model [16]

A deadly 3 phase LLL-G short circuited Fault was placed near major generating unit and just cleared after that. During fault and outing of major generating condition, based on this basic input data to bagged tree classifier gives output to have "DG1" start output so that to remain in stable condition. The input to the classifier is as follows,

Renewable controllable power = 36 KW

Controllable non-critical load= 37.2 KW (full demand- worst condition to have biggest chance to have proper restore plan)

Type of Fault = "LLLG"

Fault Voltage = 0.7812 p.u.

POS = 61.20 %

And Classifier output = "DG1"

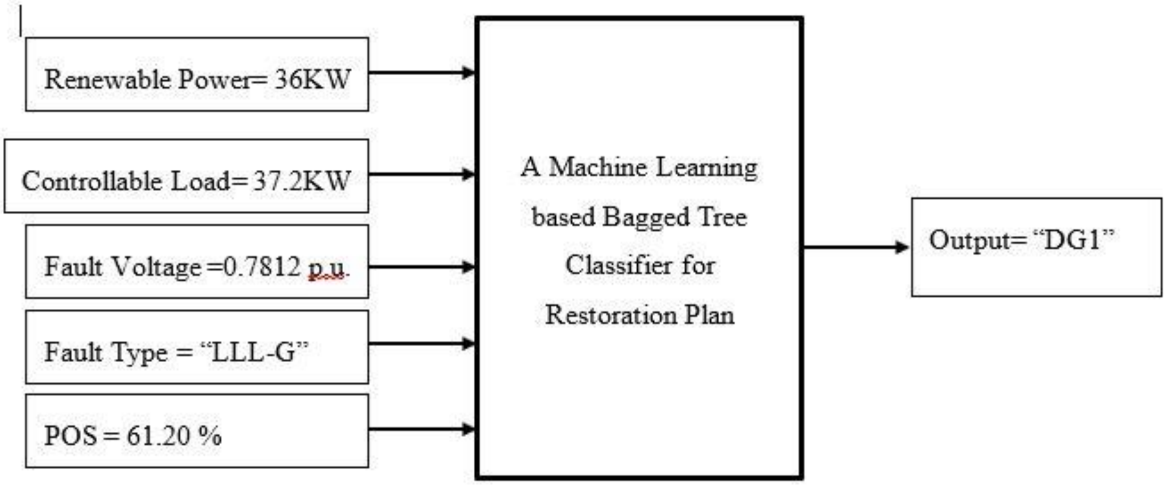

Figure 16: Input-output sets of ML Bagged tree classification

4.5 Restoration plan with GA

The capacity of DG by economic dispatch shall be calculated using GA algorithm.

$$Objective: Min\left(\sum_{Dg1} C_i(P_{dg1}) * \sum_{i=1,2,3} (Vpost - Vfault)^2\right)$$

Subjected to:

$$P_{Load} + P_{Tloss} \leq \sum_{i=1}^{n_{ren}} Pren_i + P_{Load\_Schedding} + P_{dg}$$

$$Pgren_i \leq PGren_{i,max} \ [26,24,12]$$

$$0.95 < V_{post} < 1.05$$

$$I_{12} < 10 \text{ A}$$

$$I_{23} < 10 \text{ A}$$

$$C_i = 1$$

GA steps are population initialization, evaluation cost function, selection variable, crossover and mutation.

Dg optimal size = 16.2 KW (~20 KVA) at BUS-1

TL Loss = 1.857 KW

Total Active Load = 58.4 KW

Total Reactive Load = 43.7 KVAr

These results shows that 3 bus computational model with LLL-G near Urja khola plant fault has successfully restored with post fault bus voltage with 1.0 p.u., 0.9631 p.u., and 0.9583 p.u. in GA optimized model. 3 bus has during fault voltages are 0.78 p.u., 0.87 p.u., and 0.92 p.u.

The comparison of normal, during LLL-G fault, Fault with load curtailment option in BUS-1, GA optimized restoration bus voltage has clearely visualized in figure 17.

Table 4: Baglung Microgrid bus voltage for different Scenario

S.N.	Condition	Bus-1 Voltage	Bus-2 Voltage	Bus-3 Voltage

1	Normal pre fault steady Condition	1.0	0.96602	0.9815
2	With LLL-G Fault	0.7812	0.8706	0.9211
3	With LLLG fault and Load Curtailment L1	0.8412	0.8835	0.9412
4	GA Optimized post fault restoration bus Voltage	1.0	0.9631	0.9583

Figure 17: Bus Voltage Chart with different Scenario.

V. CONCLUSION

The standard GA based optimization system is manipulated using the machine learning based classifier and comprehensive results are achieved. Machine learning algorithm driven optimization model for restoring a stand-alone micro grid after a major short circuit fault, is demonstrating a very promising outcome.

1. A Bagged tree ensemble class ML based classification has accuracy 93.20% with ROC of AUC 0.98 for proper restoration stand-alone microgrid has achieved.
2. This study demonstrates a probabilistic optimization model for restoring a power system after a major three phase fault.
3. A standard GA-based cost-effective optimization system for catering, processed using a machine learning-based classifier, and comprehensive results were obtained.

VI. REFERENCES

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