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A machine learning based optimized energy dispatching scheme for restoring a hybrid microgrid

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ABSTRACT

A microgrid operated in stand alone mode is highly vulnerable to instability when the integration of intermittent energy sources are considered. If a short circuit fault occurs in a microgrid while operating at its design limit, often cost effective system recovery becomes a challenging task. Under such contingencies predictive analysis can be used to strengthen the system restoration schemes. In this study, a system based on machine learning algorithm is implemented to forecast the security of a standalone microgrid and based on the forecasting, schedule multiple backup diesel generators under the contingency of loss of a major generating unit. The underlying objective is to maintain the voltage stability with an optimized economic dispatch scheme, right after clearing a critical three phase short circuit fault. Finally, a promising set of outcomes are observed and discussed.

1. Introduction

Maintaining bidirectional power flow often introduces security issues in the modern microgrids [1]. The advent of large scale solar power generation in residential areas as well as integration of large scale wind energy sources contribute even more to this security. A three phase fault in such a stochastic scenario can easily cause protection system failure leading towards cascading outages. Thus a renewable powered microgrid demands novel ways of energy dispatching methods [2]. Traditionally, under these conditions a central station addresses the tertiary regulation that typically has an interval of 24 hours. However, in a modern microgrid integration of distributed generators (DG) is compelling to adopt a more local, decentralized approach [3]. It is because long term planning often is prone to large scale errors leading towards service interruptions. The alternate approach thus, would be to build short term forecasting systems of the non dispatchable energy sources [4]. One of the most sought out methods in this field is the application of machine learning algorithms [5–7]. However, most study limits itself in analyzing the accuracy of the algorithm by comparing actual and forecast data. Thus very few study has been conducted to forecast power system security in order to take service restorative (SR) measures [8]. On the other hand considerable efforts have already been made to improve SR plans by implementing multi agent based systems (MAS), advanced metering infrastructure (AMI), knowledge based systems, linear programming, progressive hedging (PH) etc [4,9–11]. These methods are computationally complex and often are not suitable for uncertain fault durations, involving integer decision variables such as a binary indication of the presence of rotor angle instability. This issue can be resolved by taking into account two types of uncertainties, i.e., a critical fault during a vulnerable and non-vulnerable periods. These periods then can be further decomposed into multiple scenario based stochastic programs [8]. However, such method would demand accurate forecasting of the system security and integration of that forecasting with the available data in an online basis. The previous studies often ignored this integration of post fault security assessment with the demand and generation data obtained from Distributed Resources (DR). Such integration of data is carried out after the stability is achieved which means this relationship is ignored during the period while addressing a critical fault [12]. This objective is attained mostly by curtailing loads. To minimize the service interruptions understanding the security of the system is a necessity. If the generation data is updated online, system security can be measured dynamically [13,14].

This study intends to bridge this gap between security forecasting and service restoration plans by implementing a novel architecture. The key argument of this study is to take advantage of heuristic search over the logic reasoning or empirical judgement [15]. The study implements a predictive analytical method that forecasts the vulnerability of a system if a critical three phase short circuit fault occurs at that instance. The prediction is made

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online, based on the available wind power, solar power and the non-critical (controllable) loads. Machine learning driven optimization is used to implement an autonomous restoration scheme after a critical three phase fault followed by loss of a generation. The proposed method takes into account the distributed generations and demands in order to predict the system security. The security assessment is carried out within short intervals considering the possibilities of a major three phase fault takes place in the near future [16,17].

This analysis explores the idea that under different energy demand and distributed energy generation, the impact of a three phase fault can either be critical or non-critical [16]. The proposed method figures out that criticality and prepares a set of optimized contingent scenarios for restoring the system. The algorithm is based on machine learning that manipulates an optimization platform in order to achieve lowest possible operating cost after ensuring voltage quality throughout the network in a post fault contingency [17]. The goal is achieved by implementing an ensemble of bagged decision tree based system to do the forecasting followed by a genetic algorithm (GA) for the service restoration. Many previous studies have successfully implemented security and reliability indices for system analysis [18]. This study takes a similar approach to measure system security by introducing a binary security index called Probability of Stability (POS). The index considers several scenarios of short circuit faults resulting in isolating a generator bus in the affected area [17]. The database of POS is prepared by a Monte Carlo simulation method. The stability analysis carried out in this study, has a hierarchical structure with a primary goal of restoration and a secondary goal of economic dispatch. The optimality is discussed in terms of stabilizing a system with lowest possible operational cost.

2. The micro-grid model

Two different models have been used in this study. For building the method a small scale system is used. To understand the impact of the proposed method in larger networks, an IEEE-39 bus 10 machine system is used. Both are shown in Fig. 1.

The smaller network has one hydro turbine based synchronous generator, two backup diesel generators (synchronous) of **G1=4 MW** and **G2=3 MW**, one asynchronous generator representing the wind farm **3 MW** and a voltage source converter based solar power plant **5 MW**. The loads are lumped on a common transmission grid. This distribution approach is inspired by the microgrids used in [9,19]. However, this model differs in dividing the loads into two parts; critical and non critical loads [20]. The critical loads are comparable to the base load of a system that has to be met. On the other hand non critical loads are often considered to have flexible levels in any demand response program, specially in an islanded mode [21,22]. Such flexibility allows load-shedding or curtailment at users discomfort. For simplicity it is assumed that no curtailment cost has to be paid by the service provider. The total demand in this microgrid is higher than the total capacity of the synchronous generator models used as power plants. It signifies that the power quality and stability of the system time to time depends on the wind power plant and the solar power plant. The wind power plant is modelled as an induction generator-based variable speed wind turbine. The solar power plant is modelled as a current source and placed closer to the residential load. The three phase model has diodes, internal resistance and leakage current followed by a voltage source converter (VSC) as presented in [23]. The VSC based solar plant is only implemented as an intermittent energy source. These two distributed and intermittent sources do not have any type of power system stabilizers installed in them thus maintaining stability in the system is carried out through the synchronous generator based models. To capture the full dynamics of bidirectional energy flow both the solar and wind turbine plants are designed not to have any energy storage device.

The generator buses are represented using the typical second order swing-equation;

$$M_i\ddot{\delta}_i + D_i\dot{\delta}_i = P_{mi} - P_{gi};\, i \in generator_{1:3} \tag{1}$$

Here, δ_i is the generator rotor angle, P_{mi} is the mechanical power input, P_{gi} is the electrical power output, M_i generator's inertia coefficient and D_i is the generator's damping coefficient. The overall operation is subject to [17];

$$P_{gi} - P_{li} - \sum_{j=1}^{3} U_iU_j(G_{ij}\cos\delta_{ij} + B_{ij}\sin\delta_{ij}) = 0, \tag{2}$$

$$Q_{gi} - Q_{li} - \sum_{j=1}^{3} U_iU_j(G_{ij}\cos\delta_{ij} - B_{ij}\sin\delta_{ij}) = 0, \tag{3}$$

In order to test the security of the system and develop the probability of stability (POS) database, a critical three phase fault is placed near the hydro station.

3. Data model

To build up the forecasting system three data models for wind power, solar power and non-critical load have been prepared. **N** number of random data points are generated using those models. Then a Monte Carlo based simulation is used with the data points for developing the Probability of Stability (POS) table. Each scenario has a three phase fault in it.

3.1. Wind energy model

For simplicity the wind power generator only considers wind speed as a variable.

$$P_W = \frac{1}{2}\rho A v^3 C_{total} \tag{4}$$

where P_W is active power output, C_{total} is overall efficiency of the wind turbine, ρ is air density, A is swept area and v is the wind velocity. The wind velocity at any certain height is calculated by $v_h = v_r(h/h_r)^\alpha$ and α is the power law exponent. Where, v_h is the speed at hub height, v_r is the speed at reference height.

3.2. Solar energy model (photovoltaic)

To simulate the characteristics of solar power generation the following irradiance based photovoltaic cell model of a solar cell is used:

$$I = I_{ph} - I_s\,[e^{\frac{V_{OC}+IR_s}{NV_t}} - 1] - I_{s2}\,[e^{\frac{V_{OC}+IR_s}{N_2V_t}} - 1] - \frac{V_{OC}+IR_s}{R_p} \tag{5}$$

$$V_{OC}(t,\beta) = V_{OC-STC} - K_V T_C(t) \tag{6}$$

where V_OC is the open circuit voltage of the PV-module, I_{ph} is the solar-induced current that can be further explained by $I_{ph} = I_{ph0}\frac{Ir}{Ir0}$ I_r is the irradiance in W/m^2, I_{ph0} is the solar current obtained for irradiance I_{r0}; I_s and I_{s2} are the saturation currents of the Diode-1 and Diode-2 inside; N_1 and N_2 are the quality factors diodes; $V_t = \frac{kT}{q}$ is the thermal voltage, (k is Boltzmann constant, T_C is device temperature in Kelvin) and K_V is the open circuit voltage temperature coefficient; $T_C = T_A + (NOCT - 20deg)\frac{I_r(t,\beta)}{800}$. R_s and R_p are the series and parallel resistances [24]. β is the tilt angle and T_A is the ambient temperature. The overall output power from the plant is given as; $P_array(t,\beta) = \eta_{PV}N_SN_PP_{PV}(t,\beta)$. Here, N_S and N_P are the total number of modules connected in series and parallel, η is the conversion