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Self-healing Capability against Power Outage in Smart Grid

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ABSTRACT
An important feature of the new Smart Grid is self-healing capability against major power outages, transient instability, and power quality disturbance events. Of those probably the most damage done is by a power outage caused by a natural disaster. Just recently hurricanes like Dorian, Elsa, Ida, etc. caused large-scale blackouts. This is not to mention the most frequent bad weather, unexpected tornados, and hurricanes categorized under the rank of two. In those cases, the smart Grid should have a prediction and estimation capability for rapid maintenances. Most works in this area concentrate on learning a machine from historical logs, learning environmental measured data from satellites, or surprisingly enough but sometimes analyzing measured electromagnetic signals that are above the normal background activity of the earth. In the frequent case of power quality disturbance and transient instability, many works in the literature enable self-healing capability. But devices need to be software-defined equipped with cognitive capability that can be remotely reconfigured.

Keywords-- Harmonic Distortion, Smart Grid, Power Quality Disturbance, Transient Instability

INTRODUCTION

The smart grid is an electric system that uses information, two-way cyber-secure communication technologies, and computational intelligence in an integrated fashion across electric generation, transmission, distribution to achieve a system that is clean, safe, secure, reliable, resilient, efficient, and sustainable [1]. An important feature of the smart transmission system is upgrading the reliability [2-3] and flexibility [4-5] of the traditional transmission system. Deploying state-of-the-art HVDC or EHVAC across the whole grid is not cost-effective; rather the better option is to add smart features [6-9] into the existing AC transmission system. Any adjustment to an electric grid must, however, meet the following four basic requirements: capacity defined in terms of satisfying the increasing demand for electrical energy; reliability definitions available in the literature [10], flexibility definitions available in the literature [11], efficiency defined in terms of the principle that energy has to be saved from production up to consumption and sustainability defined in terms of supporting the integration of low carbon energy sources. It should be noted here that the flexibility requirement requires the safe interconnection of distributed generation units and energy storage including integration of heterogeneous energy generation at any point on the system at any time. The reliability requirement requires uninterrupted power flow anytime and anywhere. For a smart grid to operate reliably and efficiently it should have a self-healing capability against power outage, power quality disturbance, and transient instability.

In cases of abnormality and power quality disturbance events, the central grid management system must initiate a self-healing process. It involves isolating faulted line sections to restore services to upstream and downstream unaffected line sections thus preventing customers from experiencing major outages [12]. Repeated measurements [13-15] indicate that fault occurs in the following three cases: during power quality disturbance, during overloading, when a power flow exceeds beyond a certain reference value caused by unpredicted demand-side management, or during contention caused by abnormal static line rating when conductor temperature exceeds the normal value which causes conductor sag. In these cases, an intelligent fault monitoring system within the

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central grid management isolates the faulted line to reroute power flow automatically. This in turn requires electronic devices not only to be digital [16] but also to be equipped with intelligent capabilities.

First, let us see features of a smart transmission system singling out only the overhead transmission system. Overhead transmission conductors in smart grid unlike the traditional AC, HVDC, or EHVDC consist of composite conductors or superconducting wires capable of withstanding high temperature. These conductors have the properties of greater current carrying capacities, lower voltage drop, lighter weight, and greater controllability [17]. State-of-the-art CTs and VTs can protect themselves from saturation caused by faults, monitor cooling systems, and can decide on tap changers of transformers in real-time [18-20]. All devices throughout the smart grid should have the capability to talk to each other through the advanced network infrastructure. The communication can happen through the already installed TCP/IP internet, but because different nodes in this case MAC enabled electrical equipment in smart grids require different communication necessities, different protocols [21] can be defined for the exchanged packet between nodes and the central grid station.

To accomplish all of these tasks, equipment throughout the smart grid should have the cognitive and reconfigurable capability. Cognitive is the ability to sense information from the surrounding environment to analyze and learn the sensed information to make decisions. To accomplish this task electronic device needs to be software-defined where most of the processing and decisions will be made via software. This in turn equips the equipment with reconfigurable capability: the capability of adjusting operating parameters in real-time without any modification on hardware components. For instance, distance relays of the future can reconfigure ampacity online in real-time (see section 4).

In this paper, a discussion on how to add self-healing capabilities to the existing AC transmission line is presented to point out future research gaps. The rest of this paper is organized as follows Section 2 of this paper presents the self-healing process during major power outages. Section 3 of this paper deals with power quality disturbances. Fault monitoring and diagnosis system in case of small-scale transient instability are presented in Section 5. In the end surveys to the solutions of over-current due to overloading along with how the smart grid transmission system handles excessive temperature is explained. The paper ends with concluding remarks pointing out future works.

POWER OUTAGES

Major power outages in this paper refer to those outages that impacted at least 50000 customers or caused an unplanned firm load loss of at least 300MW. Power outages thus occur either due to critical equipment failure in the grid, natural disasters, or cyber-physical threats. In such cases, the smart grid must be resilient. Resiliency in this context is the ability of the smart grid to respond to and recover from outages through an iterative process of sensing, anticipation, learning, and adaptation to all types of hazards and disruption [22]. The crucial queries while ensuring resiliency would be whether or not the supply has been disrupted, if so by how much, and the capacity to restore power quickly [23]. Hence, include early detection of low probability high-risk extreme events including natural disasters and man-made attacks, and the corresponding risk assessment to mitigate the damage rapidly [24]. Thus, one needs to assess the following points.

Natural disasters damage electric power system components causing cascading failures. The most probable cause of such damage is hurricanes in the Western Atlantic and Eastern Pacific Ocean Basins, cyclones on the west Indian ocean, and Typhons on the east pacific or strong earthquakes above a magnitude of 4.0 on the rector scale. The damage will be especially significant in the generation and transmission units, because distribution systems are maintained rapidly to large-scale disasters, except for unexpected high-intensity rapid tornados. Hurricane Sandy as an example in 2012 cut power to 8.2 million households in 17 states on the eastern shore of the U.S [25]. Hurricanes Irma, Michael and Maria, and more recently Hurricane Dorian resulted in power outages that affected millions of customers and led to major social and economic disruptions throughout our communities. In general, more than 1500 hurricane-induced outages are reported across the content of the USA starting from 2000 [26]. A simple fact is the longer the outage duration, the greater the incurred losses. Repeated measurements show that Hurricanes inflict damage in two different ways [27]. First, the gushing flow of water will flood the low-lying coastal areas, damaging substations. The second is the damage to the power generating equipment due to fastly rotating winds. Even on weakened hurricanes categorized under rank two, the most reliable underground transmission and distribution system will be flooded from heavy rain causing a cascading failure. The obvious solution is prediction.

Predicting hurricane impacts on the smart grid before landfall can improve pre-storm planning efforts for utility companies. Utilities in this case must weigh the anticipated impacts and estimate how much assistance they will need [28]. The primary way of modeling the impact of hurricanes in the literature on the electrical power system is machine learning-based approaches. These models use geographically detailed damage data from past hurricanes and weather data like storm surge, wind speed including direction, and cloud density from satellites to estimate post-storm restoration effects so that the required crews and materials be positioned as close as possible to the area of highest damage. As an example, in [29] an estimate of the number of poles and transformers needed for replacing the damaged ones is fitted against historic data using simple linear regression models. Hence a prediction algorithm in smart grids needs to be trained using the collection of outage reports and repair logs that utilities keep. To systematically process these historical data recent advances in the fields of Machine Learning are required. This was proven to be effective in [30-31] where average outage duration and restoration time are predicted. But the accuracy of these predictions is more dependent on the input features than the real algorithm precision performance. For this particular reason, most of the work in this area is concentrated on correctly identifying the input factors that contribute to accurate prediction. The gap here is the lack of accurate historical data on substations located at certain GPS: degree, minutes and seconds, or longitude and latitude.

In that case, the main feature that must be considered are storm surge, the volume of water that the hurricane may force inland, the maximum sustained wind speeds, the exposure time to tropical storm winds, and the land area swept by the hurricane[33-34]. To a surprise, variables that are not features of the weather are also shown to be effective in restoring service quickly. One of such is biodiversity-related variables like plant specious type. This was due to a particular observed fact that about a quarter of outages for a mid-voltage overhead line are caused by tree failure accounting for different specious [35]. But in the work, the prediction improvement wasn't dependent on interspecies but also intra specious. In [29] at a wider geographical scale, it is observed that as the relative abundance of Sweetgum and Loblolly Pine tree species increased; the number of outages tended to increase. In contrast, increases in the relative abundance of Water Oak and Chestnut Oak, by the way, they are of the same spacious, did not result in more outages. These roots to the suggestion that certain oaks may be more resistant to uprooting or snapping when subjected to strong winds. However, predicting hurricanes damage at a certain probability requires a large amount of data to be crunched in supercomputers.

Lightning is also the other cause of power outages. It affects the performance of power lines by creating a transient overvoltage that causes flashover on the power line either in a direct stroke, when lightning hits a phase conductor or in indirect strokes when lightning hits a point in the vicinity of the transmission line [36]. Direct stroke generates an impulsive transient which causes a fault with the accompanying voltage sags and interruptions. The resulting lightning surge can be conducted a considerable distance along utility lines and may cause multiple flashovers at poles [37]. On average approximately 10-14 cloud-to-ground lightning flashes strike the glob each second causing momentary interruption [38]. Besides this Ground Flash Density i.e. geo-locational variation of lightning strikes, the probability of a direct strike at poles increases linearly with tower height, thus high voltage lines are subject to direct strikes more than medium voltage or low voltage lines[36]. Acknowledging this risk, surge arresters are installed at towers which effectively eliminates the overvoltage. In an indirect lightning strike, lightning may hit near the line causing an impulse by the collapse of the electric field or it may hit the ground at substations causing the ground reference to rise considerably. This forces current along the

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grounded conductors to flow into a remote ground passing through sensitive loads. An interesting case is the low side surges in transformers [39]. From the wide variety of field observations available, it had been discovered that many lightning-induced transformer failures of the primary or high voltage winding were induced from the low voltage side. Transformer designers named this phenomenon low side surges because from the perspective of the distribution transformers, the surges entrees from the LV side though the lightning stroke is located at the HV side. Also from the customer's point of view, it appears to be an impulse coming from the utility. Investigating these kinds of lightning surges into the case-sensitive load is an interesting gap. Some solution for low side surges is presented in [40].

The other main natural disaster that must be considered is earthquakes. For example, a magnitude of 6.7 earthquakes on the island of Hokkaido damaged a 1.65GW power plant leaving 3 million houses in darkness [41]. Predicting earthquakes before it happens is a well-explored at the same time interestingly debatable area with many hypothesis and particular solutions. For example, contrary to many developments in the area, there is a theory that earthquakes can't be predicted, the root traced at the argument [42]. The primary means of prediction however is based on the analysis of observed precursor seismic signals [43]. These seismic signals can be enlarged or nulled before a major earthquake happens. The former is the case of Foreshocks where a series of sesmic events of magnitude higher than the magnitude of the normal background seismic activity. The latter is Sesmic Quiescience, the apparent lull in the normal seismicity of a region. To a surprise, an attempt to predict an earthquake pattern is presented in [44] using a completely different way. It is based on plotting extremely Low-frequency electromagnetic waves in the range of Heartzs using telescope satellites or simple giant ground antennas. The prediction algorithm and accuracy, in this case, are not that much important. The majority of the work in this area is based on the usual feature extraction of big data logs. Though doubt on the accuracy of this prediction besides the usual regression or approximations, any machine learning algorithms [45-49] can do the task effectively.

In general, considering the number of papers, current resiliency works against natural disaster relies on the already existing domain expert knowledge and its analysis, the solution being semi-manual coordination between the system operator, and transmission and generation parties. Therefore, the focus in this research area is in infant mode.

POWER QUALITY DISTURBANCES

Power quality deals with any deviation in magnitude, frequency, or purity of the generated sinusoidal voltage. The causes for this poor power quality are categorized into two groups: i) actual loads and ii) subsystems of transmission and distribution systems which result in voltage swell and sags, harmonic distortion, transients, and flickers. Smart grid transmission systems accurately classify and mitigate power quality disturbances and deviations to a sufficient level of accuracy. Since one can't tune the magnitude, frequency, or purity of the current on the already installed transmission line, correction in the power quality is achieved either by tuning the supply voltage or by inserting current limiting equipment [37]. In the subsequent paragraphs, the causes of power quality disturbances are discussed.

The most common causes of power quality disturbance are Voltage swells and Voltage sags. A voltage sag is a short-term about 30 cycles or a long-term about 5s reduction in RMS voltage caused by a sudden increase in load impedance or source impedance. The corresponding voltage swell is a short-term about 30 cycles or a long-term about 5s increase in RMS voltage caused by a sudden reduction in load impedance or source impedance. Voltage sags and swells are corrected in real-time using state-of-the-art FACTs devices [50]. The correction for instance can be done at substations using Ferro resonant transformers which yield almost constant secondary unit voltage against varying primary unit voltage. Or if one prefers to regulate the voltage at constant amplitude then one can use magnetic synthesizers or superconducting magnetic energy storage. Superconducting magnetic energy storage devices especially alleviate voltage sags in less than 1 cycle. This accuracy is due to the energy induced by superconducting magnets. It is because the current flowing through these lossless conductors releases energy instantaneously [51]. Alternatively for a typical distribution system in the USA simple low-cost options of UPS systems and dynamic voltage regulators are available but their functionality is restricted to low or medium voltage.

But compensating voltage sags and swells come at a cost. The various nonlinear FACT devices and IEDs produce a frequency component that is an integer multiple of the fundamental frequency. Note here that this harmonic distortion adds a deviation from the fundamental frequency component. It is mainly caused by the shunt FACTs device because the nonlinearity of the series FACTS device is insignificant. The reason being the short circuit impedance between the source and load is mostly resistive [37]. The other sources of harmonic distortion are Power converters, transformers, PF correction capacitor banks, and nonlinear loads. Hence, research in the state of the art electrical and electronic development is to reduce the nonlinearity of shunt FACTS devices. For instance, it transforms the most common electrical equipment in the transmission system, the leakage impedance is linear to a sufficient accuracy but the shunted magnetizing impedance is the source of harmonic distortion. Though the mostly available common power transformer is designed to operate below the magnetizing saturation characteristics [52], sometimes transformers operating at normal conditions are also sources of harmonic but this distortion is typically less than 1% of the rated values. Individual harmonic distortion at each substation, in this case, is ignorable but the effect will scale up on utility distribution systems where hundreds of transformers are in operation. Here, special emphasis should be given to triplen which are the odd multiple of the 3rd harmonics [53]. The design problem, in this case, is that triplens cause overheating on the Y-Y connected transformer; experienced one may think this can be alleviated by the delta connection at the secondary side. But the problem won't be solved by rearranging the connection. The delta winding provides ampere turn balance so that triplens will flow but it will remain trapped in the delta side and do not show up on the line current. The only solution is to use isolation transformers [54].

Besides the already discussed causes in the smart transmission system, harmonic distortion happens at distributed generation units. Especially wind power generation units and solar generation units are the major sources of harmonic components [55]. In Europe, where carbon-neutral clean energy generation units are abundant, harmonic distortion due to generation units on a transmission line is rare since the sine wave at the central stations is accurate to a sufficient level. Since carbon-neutral energy generation units aren't abundant in the USA, the main source of harmonic distortion however happens to be the nonlinear power electronic loads and energy-saving nonlinear loads at the consumers. In such a case the smart grid should maintain the necessary observable quantities [56] in a database for rapid maintenance. The maintenance is tracing the source of the harmonic current. Note that harmonic current flows from the source into the generation units or the capacitor banks. One can determine the flow into the generation units or the capacitor banks by looking at the harmonic spectrum. In the latter case, monotonic frequency components dominate the other harmonic components to a significant level. But in the former case, the harmonic source can be traced by installing PMU which measures the entire spectrum of the current that passes through the shunt nonlinear loads. This data kept at the central grid management system can be correlated to a set of harmonic profiles to shunt identify the source [57]. The location can easily be traced from the GPS-stamped frames. Alternatively one may treat the problem as a big data problem where the GPS stamped harmonic frequency spectrum is learned to identify the location. Any function approximation, classification, or regression machine learning algorithms can do the task. Unfortunately processing a large amount of data is time-consuming and is vulnerable to cyber-physical treats.

To summarize, the main problem discussed here is to accurately locate nonlinear loads that contribute to a significant deviation from the fundamental frequency generated at substations. It is mitigated based on commonly available techniques in [58] or in [54] which contains a harmonic distortion model of the power transformer. If a utility company fails to do the task, the burden is on the customers. From the end-user point of view, users have to limit their harmonic current emissions to a range of values specified in [59] at the point of common coupling with other consumers. Immunity standards are also set down for the disturbance levels which equipment should be capable of tolerating without undue damage or loss of function [60]. Another standard for compatibility levels has the function of enabling coordination and coherence of the emission and immunity standard [61]. Besides the presence of harmonic distortion, deviation of the fundamental frequency from nominal values at a much higher scale happens due to the integration of heterogeneous energy generation units. This power frequency variation is corrected by the central grid management system to acceptable limits. Two main levels define these limits: the operational limit which is equal to ± 0.2 Hz and the statutory limit which is equal to ± 0.5 Hz [62]. Under a significant drop or increase in the frequency, a disconnection by low-frequency relays is remotely invoked.

TRANSIANT MONITERING AND DIAGNOSIS SYSYEMS

Perhaps an important capability of the smart grid is the self-healing capacity against transients. An intelligent fault monitoring and diagnosis system within the central grid management system classifies and locates symmetric and asymmetric transients for rapid restoration of service.

Fault Classification

The fault classifier takes zero sequences, negative sequence, or positive sequence digital converted current or sometimes voltage transients. Phasor Measurement Units (PMU) installed throughout the grid sends this digital transient data to the fault monitoring and diagnosis system. The data will be analyzed to differentiate between symmetric faults i.e. triple line to ground (ABC-G) or triple line to line faults (ABC) and asymmetric faults i.e. line to ground (A-G, B-G, C-G), line to line (AB, BC, AC) or double line to ground faults (AB-G, AC-G, BC-G). This data should be time-stamped and GPS stamped to avoid time synchronization problems encountered during measuring phases [61]. The intelligent fault monitoring and diagnosis system upon classifying the 11 types of faults will initiate a self-healing process. The process includes detecting, classifying, and locating.

For decades classification of faults or fault analysis in classical textbooks is done using the well-known symmetric component theory. The theory quantizes symmetrical component phasors in cases of symmetric faults or zeroes, positive and negative sequence phasors incases of unsymmetrical faults [62]. However, the theory isn’t appropriate for real-time grid protection. For these kinds of problems computationally intelligent algorithms are preferable. Fault classification can be done using the many algorithms in the literature like expert systems [63-76], classical classification algorithms [77-79], Artificial Neural Network [80-82], or Hybrid Algorithms. However, these areas are sufficiently saturated to find a new gap.

Fault Location

The identification is shortly followed by a diagnosis procedure. In the simplest case of temporary faults, a probe signal is sent to check the continuity of the line or the closeness of the circuit. For permanent faults, an alarming procedure including sending messages to operators via an ad-hoc network infrastructure is initiated to clear the fault manually. The message consists of the type of fault and the location of the fault. Locating faults in some literature are approached as a classification problem where post fault phasor data are gathered to determine the optimal hyperplane. Artificial neural networks, support vector machines, or any other classification algorithm can be used to plot the boundary. But the precision is restricted to discrete spans in the range of multiple km, for example [83,84] proposed MLP with a span of 10 Km, [85, 20] proposes LDA with a span of 10 KM, [86] proposed SVM with a span ranging from 10-25 Km, [87] proposed SVM with a span of 30 km. But classification algorithms won't locate the exact GPS coordinate; instead, they provide a span of locations. In the past accurate location have been computed using impedance-based methods [88, 89-92]. Impedance-based fault location algorithms, well explored in textbooks, calculate the exact location estimates from the transient data captured by PMU at one end of the line. It is to calculate the fault impedance seen from one endpoint in one impedance-based method or seen from the two terminals of the line in the two endpoint impedance methods [89]. But impedance-based methods require accurate estimation of lumped

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line parameters which in some cases is difficult due to the non-homogeneity of the transmission line. Recently with the advancement of DSPs, GPS, and clocking technology, the traveling wave-based method is gaining more popularity. The method is also applicable for EHVAC, HVDC, and Underground Transmission systems.

Travelling wave-based method is based on the observation that when a fault occurs, high-frequency waves called surges propagates in the form of reflection and refraction away from the fault point (see figure below) in both directions towards the terminals of the line at velocities very near to the speed of light [94]. The task of the location algorithm is therefore to detect the arrival time of wave heads. The location is easily calculated as the product of arrival time to the propagation velocity i.e. speed of the wave head [95]. The propagation velocity is estimated as $\frac{1}{\sqrt{LC}}$, where L is the inductance per unit length and C is the capacitance per unit length. Both of which are estimated based on the conductor type. For this particular reason, non-homogeneity of the line will introduce precision errors.

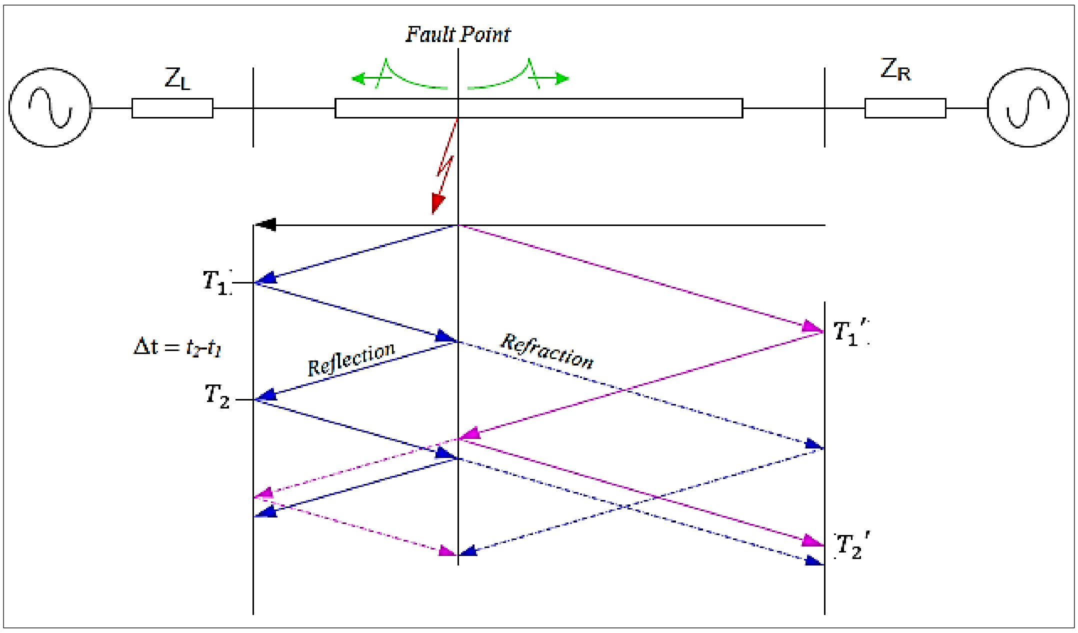

Figure 1: *Lattice diagram for the propagation of fault-induced traveling waves.*

Besides the nonhomogeneity of the line, the type of weaves also determines the accuracy of the location. According to the IEEE Std C37 guide, five types of travelling waves are recognized [89]. In Type 1 travelling wave, the arrival time of wave heads is measured by recording the reflection of wave heads at one terminal $(T_2 - T_1)$. Alternatively, in Type D travelling waves not only the arrival time of reflected wave heads but also the refracted wave heads at the other terminal is used $(T_2 - T_1)$ and $(T_2{}' - T_1{}')$. However, because the amplitude is attenuated due to surge impedance, detection of wave heads at both terminals is difficult. In Type C travelling wave also known as time-domain reflectometry (TDM) a probe signal generated from oscillators is injected into the line exactly in the same manner used to detect faults in the underground cables. In a Type E traveling wave the injected probe signal is the transients created when a line is re-energized by closing a circuit breaker. On the fourth traveling wave method, the accuracy highly depends on the detection of wave heads at the receiving end. One way to improve detection is the use of a stop weave head signal at the remote end which is initiated when a reflected wave arrives at the other end. The resulting traveling wave is Type B travelling waves.

It should be noted here that in addition to the wave getting attenuated in amplitude at the receiving end harmonics are introduced by CTs, VTs, and FACTs devices installed throughout the transmission line. For this particular reason added to the interference of reflected and refracted weave heads at the fault location, detection of weave heads is difficult [86]. Transforming the

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signal from the time domain into analogue or digital frequency domain or wavelets [96-97] reduces such effects. Traveling wave-based fault locators are more accurate and reliable compared to Impedance based methods; However, They require advanced hardware with a high sampling rate.

DYNAMIC LINE RATING

On traditional grids, transmission lines have a fixed-line rating known as static line rating. The ampacity which is the maximum allowable current-carrying capacity without passing the conductor thermal limit is calculated based on worst-case weather conditions [98]. These conditions are ambient temperature, wind speed, and solar radiation all of which varies temporally and spatially. Several models existed for the calculation of ampacity: IEEE, CIGRE, and IEC. According to IEEE for instance the static ratings are determined from the second law of thermo dynamics [99]:

$$Q_C(T_C, T_a, V_m, \varphi) + Q_r(T_C, T_a) = Q_J + Q_s \quad (1)$$

Where Q_r is the radiative heat which depends on the conductor temperature T_C, ambient temperature T_a, wind speed V_m and wind direction φ. Q_C is the conductive heat that varies with conductor temperature and ambient temperature, Q_s is heating due to solar radiation, Q_J is the joule heating governed by the equation $Q_J = I^2R(T_C)$. The exact estimation of the quantities is found in [100-101]. From the above equation, one can drive ampacity as:

$$I_{max} = \sqrt{\frac{Q_C(T_C, T_a, V_m, \varphi) + Q_r(T_C, T_a) - Q_s}{R(T_c)}} \quad (2)$$

Traditional grids set amperage values equal to the ampacity according to the "worst-case" measurement of weather variables. The problem is a weather condition that varies by space-time causes distance relays sometimes to trip other times even to damage. Bear in mind here that in such a case, it is possible to provide service for the customer. Distance relays of the future treats ampacity as an adjustable quantity rather than a design issue. Thus, will have the capability to reconfigure amperage in real-time according to weather conditions. Reconfiguring the DLR system, in general, include three primary components: DLR sensors which measure environmental conditions like temperature, wind angle, and wind speed. Operating conditions such as nominal current and conductor sag. And finally, communication devices that receive and transmit the measured field data to a central smart Grid DLR management system. DLR systems decide the amperage in real-time and Hence configures the ampacity of the transmission line based on weather conditions [102-104].

When the current passing through the transmission line passes the reconfigured amperage an alarm is issued. Here there are two possible scenarios: in an expected case during congestion, the power flow can exceed the configured amperage or during measurement or prediction error the dynamically configured amperage may allow current beyond the safety limit which causes conductor sag [105]. These uncertainties during measurements of digital DLR sensor data include sensor accuracy, precision errors, and temporal variation of weather data. For instance, wind speed and direction can be forecasted up to 10 minutes in advance [106]. Several probabilistic models to mitigate the uncertainties are found in [107]. But probabilistic tools are limited due to either the necessity of having a given standard probability distribution for the uncertain parameters or due to the computational burdens imposed [108]. Another option is to use fuzzy models. Though fuzzy models are proven to reduce the effect of uncertainties, they are vulnerable to overfitting [109].

In addition to self-healing explained above, DLR provides our reliability. Observations [110] show that transmission lines are underutilized during congestions. This is because DLR allows the transmission line to be loaded above the static rating without exceeding the operating temperature limit and hence the nominal conductor sag [111]. This provides a higher current carrying capacity for the transmission line, thus can mitigate system congestion and reducing generation re dispatching in cases when congestion is caused by the transmission thermal limit [112]. To conclude reconfiguring amperage online in addition to protecting false trips reduces congestion in real-time. This in turn facilitates heterogeneous power integration. For example, more power is

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generated during windy conditions. DLR thus has economic benefits [101].

CONCLUSION

Smart grid should mitigate power outages in case of natural disasters such as hurricanes, tornados, or earthquakes. The method is predicting damage before landfall for rapid service maintenances. But the available algorithms in the literature are short of accurate predictions. The majority crunch detailed GPS stamped logs in high-performance CPUs at the central grid stations. Despite these works self-healing capacity of the smart grid against major power outages is in an infant state. On the other hand, the currently available algorithms in case of power quality disturbance and transient stability are saturated enough. But equipping this smart capability to the electric equipment throughout the grid requires the device to be state of the art with the capacity to be remotely reconfigured.

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