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Study of All Available Strategies Integrated in Developing an Emergency Control Plan

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ABSTRACT

To maintain power balance, changes must be made on both the demand and supply sides. The power system's operating point will be less predictable as a result of these adjustments. Designing emergency controls offline via lengthy simulations has long been the norm. New sophisticated "wide-area emergency control algorithms" are needed since power system for the future is likely to vary more. The final line of defense for grid security and resilience is emergency control of the power system. This research offers and examines several strategies for under-voltage emergency protection. The solutions explored include LTC tap changes (locking, reversing, and blocking), distribution side voltage set point decrease, and eventually, load shedding. The study also discusses how some of the aforementioned strategies might be integrated into developing an emergency control plan. The ideas are shown in a small power system with three loads with encouraging results.

Keywords : Voltage stability, Emergency Control, Deep Reinforcement Learning, Transient Stability Dynamic Breaking, Load Shedding

I. INTRODUCTION

In the literature, there are several examples of crises and preemptive management methods. It will be examined in this section which is the most crucial of all. The literature frequently makes use of one of two ways to choose remedial control measures. The first is sensitivity approaches, and the second is Optimal Power Flow (OPF) approaches. Emergency control measures are selected using sensitivity approaches, which are determined by the stability index's sensitivity when compared to the controls that are now accessible. This was the most common method described in the early literature on emergency management. The OPF methodology is based on the discovery of corrective measures via the use of an optimization process that is subject to the power system's model. This has been the most extensively researched technique in the following literature because it may take into account the nonlinear nature of the issue.

II. SENSITIVITY APPROACH

To find control actions, several linear methods have been proposed. From a power system model, it is possible to calculate the sensitivities of distinct measures of stability about the available control inputs, and then to implement these results to improve stability. These procedures are often extremely quick, which makes them excellent for use in emergencies. They are unsuitable for huge changes in configuration due to the failure of the linear assumption.

According to [21], voltage stability was improved by employing a control methodology that relied on descriptor load flow, Jacobian's least singular value. It relies on the sensitivity of reactive and active powers, and it is remedied utilizing a strategy that is based on the continuation of previous actions. As illustrated in [22], another method of improving voltage stability is to make utilization of energy functions. In this case, an index between the high-voltage and low-voltage solutions was being utilized to enhance the power stability by increasing the difference between the two solutions. The corrective action was determined by estimating the sensitivity of each variable concerning all of the controllable parameters.

Among the earliest results in the sensitivity of the load power margin (the margin of increase for a load before voltage instability emerges) were those reported in [23, 24], in which sensitivities were computed using the Jacobian's eigenvectors. Because of this, it has been common practice in the literature to use it. These results were further developed in [25, 26], where it was discovered which control direction was the most effective in the control space. The term “sensitivity” was used in [27], and it served as a framework for both identifying voltage stability and determining the number of corrective measures that would be required. Control sensitivities and linear approximations were used in conjunction with the rapid simulation of a contingency to achieve these results.

Because of this, OLTC blocking and load shedding was executed as preventative measures. [28] describes the implementation of yet another sensitivity strategy, this time corresponding to the load power margin. It was reported in [29] that this sensitivity technique has been used in close collaboration with preventive management, which was managed to accomplish through the use of a contingency list.

Sensitivity analysis is utilized to develop an emergency control system for load-shedding for the Hellenic power system, which is discussed in [30]. In [31], the aperiodic angle stability index of [18], which had previously been published, was subjected to a sensitivity analysis. Considering that load-shedding was regarded as an emergency operation, the paper made extensive use of graph-theoretic approaches to reduce the number of control activities that had to be executed.

III. TIME POWER FLOW APPROACH”

The OPF may be utilized to reveal adequate emergency controls for a given situation. When compared to the sensitivity method, which relies on a linearization of the system, the OPF may encompass the entire model and thus take into consideration the nonlinear effects. Several stability indices may be applied to the “OPF formulation” to accommodate stability margins to achieve the desired level of resistance to fluctuation resistance. This is why the sensitivity methodologies have been largely replaced by the OPF technique in the scientific literature. The OPF is utilized to confront the economic challenges associated with the operation of a power system [32]. Consequently, “OPF formulations” such as “security-constrained OPF (SC-OPF),” “Integrate Security against Eventualities,” and “Security-Constrained OPF (SC-OPF)” is used. The SC-OPF is a computationally intensive device that is utilized to retain the power system operating in a normal state of operation. On the other hand, the OPF may also be utilized to restore the cohesion of a power system [33], if necessary. A set of stability constraints may be incorporated into the OPF to compute the corrective activity required to locate a new stable operating point.

This is a big non-convex problem that is extremely hard to simplify. Two considerations for emergency control must be made: which stability indices should be used to identify a robustly stable equilibrium; and which optimization method should be used to simplify the OPF. Many different methodologies for problem-solving have been suggested in the literature. To discover local minima of the OPF, nonlinear solvers have been effectively utilized; see [32] for a bibliographic overview of the literature. In addition, meta-heuristic global solvers have been utilized widely in the literature to account for non-convexity, as shown in [34].

Significant research effort has been devoted in recent years to the implementation of convex relaxations to the OPF problem. That's massive because of the findings of Lavaei et al. [34], who demonstrated that a semi-definite relaxation can be used to achieve precision for a wide range of benchmark systems. When utilizing a convex relaxation of the OPF, it is possible to use convex optimization to find a solution to the problem at hand. Because any local minimum in a convex optimization problem must also be a global minimum, the convergence of the processes is no longer dependent on the initial estimate [35].

Using the interior-point technique to resolve the entire nonlinear OPF solution to restore solvability, became the first to do so. To restore equilibrium, control parameters such as transformer tap voltages, active power dispatching, generator terminal voltages, and load shedding were utilized. The goal was to minimize the amount of load shedding required to achieve this. Because it makes use of a conventional nonlinear solver to solve the problem, it makes no promises about the feasibility of optimality of the solution.

Particle Swarm Optimization and Genetic Algorithm techniques were implemented on an OPF with loading margin to determine required load shedding in the event of a crisis in [36], and the results showed that “Metaheuristic Global Solutions” were obtained. It was attempted to resolve the problem using the “Swarm-Based-Simulated Annealing Optimization approach” in [37], but the results were disappointing. [38] made use of a technique known as “Ant Colony Optimization.” When the stability index of [18] is used in a pseudo-OPF formulation, the load flow equations are satisfied, assuming that V /Eth endures constant all through the emergency action, as demonstrated in [39]. To obtain the answer, the method detects an algebraic solution and does not rely on any numerical techniques, which allows it to be extremely quick.

According to [40], a method for revamping a system to offer damping to prevent small-signal instability without amending the closed-loop power oscillation damping controllers has been discovered and implemented. Through an iterative process, the least dampened electromechanical mode was eliminated one at a time. This was accomplished by initially determining the least dampened mode and its sensitivity to the control variables of OPF. After that, the settings were tweaked over and over again to bring all modes below a threshold of damping. The same method is used in all subsequent articles that make use of local-solver. In [41], the topic of security against unforeseen events was also discussed. Because of the computational challenges involved, the OPF scheme for retaining small-signal stability is generally not adequate for emergency control in huge systems in general. This thesis represents a new approach to restructuring the closed-loop damping controls throughout the errors, which is described in detail.

There has been no previous research on “Convex Relaxations of Stability-Constrained OPF,” and this is a new topic in the literature. A valuable tool in the creation of corrective activities may be provided by the conspicuous qualities of providing assurances (signifies as certificates) of infeasibility or global optimality, as well as the assertion that algorithms with global convergence exist.

“Convex relaxation of the stability-constrained OPF” is thus an intriguing issue that will be studied in the present thesis.

IV. OPERATIONAL ENVELOPE

When managing power systems, it is possible to use an operational envelope that is estimated off-line, like that explained in [42], which addresses voltage and temperature stability. It is possible to implement emergency controls as controls that guide the operating point into the security region if the functional space of the power system has stability restrictions defined. In the literature, there has also been some discussion of an estimate of the operating envelope. A first-order approximation in the form of a hyperplane can be obtained using this method, and the stability boundary of the system can then be identified by using the hyperplane. With the help of specified contingencies, [43] developed a method for evaluating the boundaries of voltage, temperature, small-signal, and transient stability under specified conditions, and the results are displayed as a graph.

Accuracy may be improved by using higher-order approximations, which have been suggested. [44] shows that a second-order polynomial may be used to estimate the small-signal stability threshold. In [45], this is further improved by including second-order estimations of the thermal and voltage stability constraints, as well as security against particular situations, into the design.

Since the security areas must always be evaluated off-line for normal conditions, the operational envelope method is hard to utilize to recognize emergency controls. However, crises are exemplary by description, making them difficult to use.

In other emergency control systems, it is necessary to change or alter the underlying functioning of the existing controls. Using load shedding in conjunction with an alteration in the control strategy for secondary voltage regulation, it was possible to eliminate voltage instability, as described in [46]. It did not rely on any other metric of instability than voltage measurements, which was a flaw in the system. On-load tap-changers are critical in maintaining voltage stability. When a crisis occurs, emergency control solutions have been proposed that rely on rolling back the function of the tap-changers [47].

“Model predictive control (MPC)” has been used in the context of reducing overloads. [48] describes the design of an MPC system that reduces thermal overloads in a closed-loop manner.

V. OTHER LITERATURE

As a smart microgrid becomes smarter, so does the need to control the flow of power. Power systems’ emergency control is often seen as the last safety net for grid resilience [1] because of its dynamic decision-making under uncertainty. Power system stability depends on various “adjustable power devices”, which theoretically is only the nonlinear equations’ solution, because of power supply and demand complexity. The control of power flow has been the subject of previous studies. However, there is still a problem in implementing edge intelligence to the alteration of power flow.

Edge computing-based smart grids have recently seen an unprecedented increase, altering the idea of power management as we know it. “For smart grid applications, Trajano provides a dependable and low latency communication network” based on edge computing that allows for efficient end-to-end management of power [7]. This is different from numerous general edge computing solutions [3–4]. Barik uses an architecture that is hardware-implemented to embrace the notion of edge computing in smart grids, culminating in better performance metrics in storage demands, power consumption, and analytical capabilities [6]. Using a heuristic method, Huang presents an edge-determining framework for real-time tracking that may enhance frame rate and detection latency by a significant margin over the cloud framework [7]. Awadi, on the other hand, considers using dispersed devices cooperating through edge computing to discover aberrant samples in power consumption data in advance. An evaluation of the model's latency and network resiliency is done in this thesis. To analyze, assess, and save data on electricity use, With the use of IoT devices and mobile edge computing, Chen has developed a smart grid system capable of real-time analysis and processing huge amounts of data [9]. Edge computing may be deployed to smart grids using several architectures and frameworks described in the previous papers. However, they don't go into detail on how micro-grids might benefit from edge intelligence. For power distribution, Albataineh presents a 2-level solution that integrates the benefits of edge identification and cloud computing, whereby an engine based on learning establishes the link between both. There may be improved power grid throughput and power consumption because of this engine's ability to load-balance between the edge and the cloud.

It's worth noting that this thesis uses edge intelligence to control distributed grids, but does not analyze power flow calculations between micro-grids. The “micro-grid framework” is enormously viewed as a hot challenge in modern smart grids, along with the rise in demand for electricity services from users. [10] Yang employs “deep reinforcement learning” to construct an online scheduling technique for managing energy deployments in micro-grids with unpredictable energy generation. An economic dispatch problem in micro-grids is examined by Fang, who proposes a “learning-based cooperative auction mechanism” that eliminates a single point of inability and increases scalability [11]. Rather than using an explicit model that relies on explanatory variables to “estimate stochastic variables” with uncertainty, Ji suggests a learning-dependent microgrid scheduling approach for the management of economic energy [12]. To improve power quality, electrical stability, power quality, and peak power demand, Etemad presents a learning-dependent charging approach for micro-grid batteries powered by renewable energy. A distributed scheduling problem in the micro-grid has been solved by Liu using a collaborative reinforcement learning approach, which lessens the coupling between nodes in the micro-grid and increases the “efficiency of distributed scheduling” [14]. Reinforcement learning is used by Brida to start generating optimal scheduling solutions for given system circumstances. Using a gated recurrent unit, Dabbaghjamanesh proposes a deep learning approach for determining the optimal configuration for reconfigurable micro-grids. Reconfiguration decisions are made in real-time based on network topology factors that change over time [15]. It is shown that the use of “edge intelligence” to “micro-grid management” may boost many achievement indicators in the following studies that multiple strategies and methodologies for economic energy management have been developed. They don't, however, go into detail on how microgrids are evolving.

Specifically, Ma investigates the application issues of DL in power flow computing, gives the network topology and skilling technique of a deep neural network, and discusses how to address the problem of over-fitting. Power flow determination in massive scale power grids is a problem that Wang addresses by “integrating professional knowledge with artificial intelligence” [16]. [16] An estimating method based on a learning-based distribution is presented by Zhu to evaluate the impact of wind speed correlation across diverse wind power plants [17]. To increase the pace of determination of “probabilistic power flow” concerns, Yang has devised a learning-based method. The differences in performance across “neural networks” with different topologies are examined, and three kinds of power bus systems are utilized as an assessment benchmark. The proposed approach may significantly improve “approximation accuracy and training speed” compared to the pure data-driven deep learning strategy [18]. According to Su, a “deep belief network” may be used to regulate the power system rather than relying only on current learning-based methodologies [19]. For complicated power systems, Huang has developed an adaptive emergency control method dependent on deep reinforcement learning's feature extraction and nonlinear generalization capabilities [20]. These works explain how to utilize deep learning to the problem of calculating how much electricity is flowing. However, research on the use of edge intelligence in “micro-grids” is still in its infancy.

In terms of published research, there aren't many studies looking at how micro-grids can employ edge intelligence to calculate power flow. Edge computing's local autonomy and the inadequacy of earlier ways to deal with them have contributed to system instability since they are not well adapted to the “edge computing framework.” Based on “edge computing and multi-agent learning," our research presents a framework for power flow adjustment. Rather than attempting to address the issue of power flow synchronization, we propose a "learning-based distributed architecture" to address the problem.

As transmission systems in many countries are getting heavily loaded, voltage instability has emerged as a challenge to power systems planning and operation. To contain voltage instability or collapse, many utilities are actively considering effective, efficient, and economic solutions such as reactive support, generation rescheduling, LTC control, and, as a last resort, load shedding. In particular, under-voltage protection can serve as a safety net for stressed systems, as it is common that a period of several minutes with low voltages precedes the actual voltage collapse [1, 2]. Thus, if something unpredictable happens, or some control function fails to lead the system towards instability and collapse, Undervoltage emergency controls can save the system minimizing the impact of the instability.

Undervoltage load shedding (UVLS) is a control action, which stabilizes in most cases an unstable power system by sacrificing a relatively small percentage of customer loads. In previous publications, this protective action has been contemplated in either a static or dynamic framework. Early approaches were based on a static power flow algorithm to alleviate line [3] or equipment [4] overloads. Some practical concepts of UVLS implementation using conventional under-voltage relays are explained in [5]. Some other implemented UVLS schemes are presented in [6], where attention is given to the influence of other protection devices. Two criteria for UVLS, namely "soft" and "firm", were proposed in [7]. Further discussion by the same authors of the influence of the load models can be found in [6].

VI. CONCLUSION

Emergency control strategies that have a direct or indirect influence on power consumption are the focus of this study. When it comes to LTC control activities, there is a number to evaluate and compare. They have a significant impact on the performance of a voltage collapse protection control system, even if they do not permanently restore equilibrium. As long as the LTC is operating within its control range, tap-reversing has been determined to be the most effective LTC emergency control method. Another possible control action is to lower the voltage setpoint on the distribution lines. The LTC now has a new, lower voltage dead band as a result of this activity. As a result, the LTC's workload is lightened (at least temporarily). It is impossible to reestablish long-term homeostasis if load self-restoration is present. It is possible, however, to minimize the amount of load shedding beyond the crucial period corresponding to the theoretical minimum amount to be shed by using voltage reduction or other combinations of countermeasures. On an 8-bus power system with three loads, a combination of voltage setpoint reduction and tap-reversing is illustrated. According to the study findings, it is conceivable to create coordinated protection strategies against voltage breakdown to minimize the quantity of Undervoltage load shedding if more research is done.

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