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Synchrophasor-based Applications to Enhance Electrical System Performance in the Netherlands

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SUMMARY

This paper deals with the essentials of synchrophasor applications for future power systems aimed at increasing system reliability and resilience. In this work, several applications are presented, covering real-time disturbance detection and blackout prevention. Firstly, an advanced big-data management platform built in real-time digital simulation (RTDS) environment to support measurement data collection, processing and sharing among stakeholders is described. With this platform, a network splitting methodology to avoid cascading failures is presented and demonstrated, which upon the occurrence of a disturbance successfully isolates the affected part to avoid catastrophic cascade system outage. Online generator coherency identification is another synchrophasor application implemented on the platform, whose use is demonstrated in the context of controlled network splitting. By using synchrophasors, data-analytics techniques can also be used for identifying and classifying different disturbances in real-time with the least human intervention. Therefore, a novel centralized artificial intelligence (AI) based expert system to detect and classify critical events is outlined. Finally, the paper elaborates on the development of advanced system resilience metrics for real-time vulnerability assessment, with a focus on increasingly relevant dynamic interactions between distribution and transmission systems.

KEYWORDS

Phasor Measurement Units, Real-Time Monitoring, Algorithms, Wide Area Monitoring and Protection, Artificial Intelligence, Controlled Islanding

INTRODUCTION

Electrical Power Systems (EPSs) undergo major changes, which result from the high penetration of renewable resources. The increased amount of renewable energy has a negative impact on system inertia. Additionally, the use of more power electronics causes bi-directional fault currents, which are difficult to detect. This raises some questions: Will the existing monitoring, protection and control schemes be sufficient to cope with new system dynamics imposed by intermittent renewable resources? How to make

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the system safer and more resilient to the new phenomena (low fault currents, low inertia, harmonics, power swings and protection maloperation)?

Typically, supported by a precise time synchronisation, the synchronized measurement technology (SMT) utilizes Phasor Measurement Units (PMU) [1] to deliver time-synchronized wide-area measurements in near real-time. The SMT is the key building block of the Wide Area Monitoring Protection and Control (WAMPAC) system [2,3], which is favourable to improve system security, stability, and reliability. The conventional PMU measurements are obtained at 50/60 frames per second, which provide EPS dynamic behaviour observability within the 10 Hz range. The estimation and processing cause an unavoidable delay of at least half of the PMU sample window. Due to these properties, the conventional SMT supported protection schemes are insufficient for future operation challenges, which require a rapid response with coordinated remedial actions. Currently, the available measurement technology in the Netherlands for exercising point of wave measurements is limited to 4 kHz, and these measurements are being provided by the powerful SAS sensor [4].

In the future, novel monitoring platforms for EPS will be needed to merge PMU and IEC 61850 Sampled Values measurement data. At the same time, providing feedback to the system based upon decision-making algorithms depending on the type of disturbance will be necessary. IEEE Std 1159 [5] defines and summarizes classification methods, and IEC 61000-4-30 [6] defines classes of disturbances. These standards define the classification based on the waveform characteristic (like switching overvoltage, fault current and voltage dips).

In this paper, a novel synchronized data management platform is presented, which serves to collect various measurements in real-time with advanced post-processing techniques. The purpose of this platform is to host integrated novel protection and control schemes as well as other applications derived from real-time updated datasets. The developed platform operates in an RTDS environment and is made considering its future application to Dutch DSOs and TSO to run synchrophasor-based applications.

The paper is organized as follows. The first section presents the developed platform for data collection and hosting of various monitoring, protection and control algorithms detailed in the sections that follow. Section II refers to controlled islanding aspects and the application of controlled islanding for coordinated instability mitigation. Section III deals with the application of AI to detect and classify power system disturbances, whilst Section IV is dedicated to power system vulnerability evaluation. In this way, the new platform will be enabled to be used for the detection of electromagnetic and electromechanical disturbances. Finally, the paper ends up with meaningful conclusions.

I. CONCEPT OF A DISTRIBUTED DIGITAL DATA PLATFORM AND APPLICATIONS

Recent advances of diverse sensors to monitor hardware components with high resolution in time increased the functional and the processing capacities of the substations' high-sample-speed Intelligent Electronic Devices (IED). For data collection and distribution, fast and reliable telecommunication links, as well as scalable software platforms, are used for advanced design, operation, and planning of power systems [6]. Particularly, the advent of SMT, which enabled unprecedented observability of power system phenomena, drives the research and industry towards investments in WAMPAC [2].

WAMPAC conveys the information from grid-wide remote locations for use in advanced situational awareness applications, and system-wide coordinated protection and control schemes to improve the power system operation while providing capabilities for future improvements [7].

Typically, a WAMPAC-based digital system encompasses elements tailored according to the requirements of preferred WAMPAC applications. Generally, it consists of: i) geographically distributed data sources; (ii) local data acquisition and processing systems; (iii) a high-speed wide-area telecommunication network for remote data acquisition and sharing; (iv) a distributed or centralised data processing and visualisation platforms. WAMPAC system leverages the SMT as a key building block to deliver synchro-measurements of electrical quantities and other parameters from grid-wide remote locations [8]. It can also utilise pieces of information provided by SCADA monitoring and substation's process data such as IEC 61850-90-5 Routed-Sampled Value to gain additional insight into the status of substation's assets and power system operating state, respectively. Recent advances in cloud computing and data analytics using artificial intelligence (AI) enabled the design of cost-effective WAMPAC systems and applications. For example, Figure 1 illustrates the conceptual scheme of an advanced digital

The platform can simulate power system and telecommunication phenomena in real-time and process the measurement data of user-defined applications. To provide high-resolution observability of the simulated grid model, the IEC 61850-90-5 Sample Values (SV) and IEEE C37.118 Phasor Measurement Units (PMU) are used. SV measurements can be sent with a measurement rate of up to 4k samples per second, whilst PMU can deliver 50 measurements per second. As visualised in Figure 3, the developed software platform for data collection and processing can receive and parse IEC61850 SV and IEEE C37.118.2 measurements in online fashion, and simultaneously store them into the in-memory Redis database for buffering purposes. The measurements can be accessed by user-defined applications in Docker application containers by using Redis database connectors in various programming languages. To assure that the developed WAMPAC applications perform adequately during most critical power system disturbances such as contingencies, thorough assessment and validation of the WAMPAC system is required. For this purpose, the above presented cyber-physical platform is used as a groundwork for the developments presented in the next sections.

II. STABILITY-AWARE CONTROLLED SYSTEM SEPARATION

Modern interconnected EPS operate under increasing pressure caused by electricity market deregulation, increased share of intermittent power generation from renewable energy sources, and ageing equipment. The combination of these and other factors has led to an increased rate of severe EPS events and blackouts in recent years [11]. The latest notable examples are the system splits of the European power grid (January and July 2021), Texas blackouts (2021) and South Australian blackout (2016). The majority of large power failures are the result of an uncontrolled sequence of events that lead to system instability and subsequent operation of relevant protection. The typical blackout timeline is shown in Figure 4 [12].

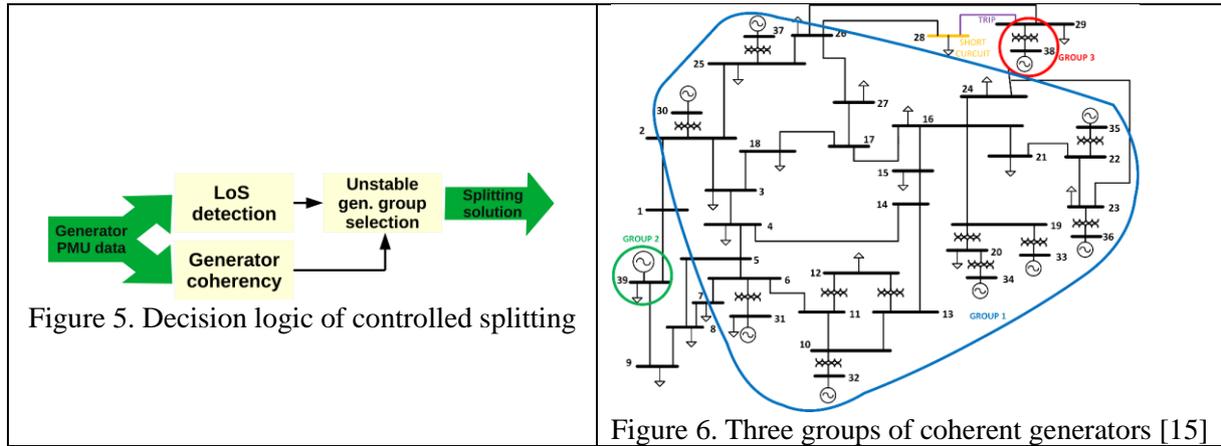


Figure 4. Typical blackout scenario [12]

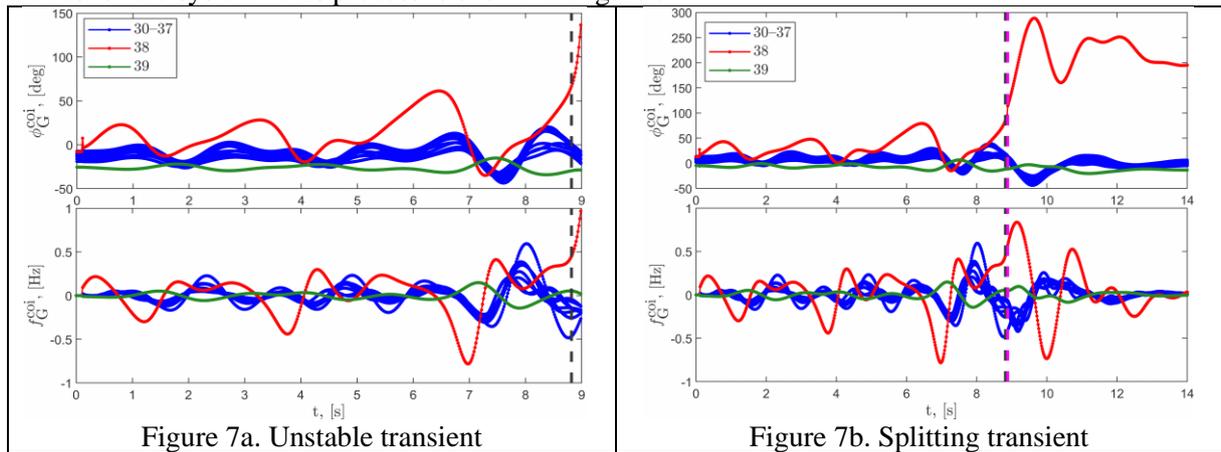
Typically, the EPS experiences a rather slow degradation of its operating condition prior to the failure (*steady-state progression* in Figure 4). This degradation is often caused by an unexpected *initiating event* occurring in a healthy power system. When the EPS reaches a vulnerable state, a single *triggering event* may cause instability or launch *high-speed cascading outages* that lead to instability and blackout. The concept of controlled system separation aims to counteract the chain of events by early detection of the instability and immediate computation of the optimal line cutset. In this way, the unstable area within the EPS is separated, while minimizing the loss of load and equipment overloads.

Controlled separation is based upon three ultimate decisions: “when to split”, “where to split”, and “what to do after splitting”. These decisions can also be viewed as the *stages* of the network splitting algorithm. The “when to split” decision should differentiate between stable and unstable transients in the EPS and possibly spot other causes of instability such as cascading outages. Additionally, this decision should detect the key EPS elements that are responsible for the instability, as this set of elements may change with time as the EPS approaches instability. The “where to split” decision is responsible for the optimal selection of EPS branches to be disconnected to isolate the unstable part of the EPS. Finally, the “what to do after splitting” decision should compute the corrective control actions (e.g., load shedding) to stabilize each island formed after splitting in the most cost-efficient manner. The second stage of the controlled separation problem can be treated as an optimization problem, an approach that is quite common in the literature. Because of this, the post-splitting control actions could be incorporated into the optimization as well, thus merging stages two and three. The first stage deals with instability recognition, whereby the scope is limited to the detection of loss of synchronism (LoS), which is the most important instability type that requires system separation. The LoS in an EPS typically occurs along the boundaries of *coherent generator groups* (CGG), the groups of generators that tend to swing together following a disturbance. Thus, CGG [13] are identified in the EPS by using the method defined in [14], and the operational experience or measurement-based coherency identification [15]. The disturbance is detected when the frequency of some generator deviates from the nominal frequency by more than a predefined threshold. After disturbance detection, the EPS is monitored with respect to several machine-related and system-

wide stability indices to track the risk of LoS. When this risk becomes very high, the system split command is activated, and the most disturbed CGG is requested to be separated from the grid. Here, the most disturbed CGG represents the set of key EPS elements that are responsible for the instability. The described decision logic of system splitting is summarized in Figure 5. For each CGG, the set of lines to be disconnected and the control actions to stabilize the islands are continuously recomputed based on recent snapshots of the power system state. The task of finding the optimal splitting cutset and control actions is formulated as a linear or non-linear integer program in order to satisfy more physical power system constraints, which explains the considerable solution time limit of a few minutes. However, the measurements during intensive power swings cannot be easily used to characterize the power balance and loading conditions in the network. Thus, the computational time delay between measurement and control is partly compensated by the duration of power swings prior to instability detection, during which no viable state estimates can be obtained. Once the first stage detects instability and the most disturbed CGG, the most recent splitting solution computed for that CGG is activated to separate it from the grid in a stable and cost-efficient manner.



A brief example of the described controlled splitting process is illustrated below. In an IEEE 39 bus network [15] as shown in Figure 6, the triggering event consists of tripping the line between buses 28 and 29 following a three-cycle three-phase short circuit at bus 28. Due to the modest network size, the selected disturbance does not contain an initiating event and cascading outages. The tripping of the line 28–29 causes growing oscillations of the generator connected to bus 38, which eventually goes *out-of-step* with the rest of the system. This process is shown in Figure 7.



The upper plot of Figure 7a displays the angles of generator terminal voltages in the system centre of inertia (COI) frame of reference (denoted as ϕ_G^{COI}), whilst the lower plot displays the frequencies of these voltages (denoted as f_G^{COI}). Both quantities can be measured by PMUs. The generator coherency estimation algorithm [15] has detected three CGGs consisting of generators at buses 30–37, 38, and 39, which are plotted in blue, red, and green respectively in Figures 7a and Figure 7b. As it can be seen in Figure 7a, the generator at bus 38 exhibits growing oscillations. Its instability is detected after 8.7 seconds from the fault inception time, which is marked by the black dashed line. The following ~ 0.2 seconds of

the sampled transient data confirm the instability. As the CGG consisting of the generator at bus 38 is the most affected one (the highest average RMS frequency value), it is supposed to be separated from the rest of the system. The resulting transients are shown in Figure 7b. As it can be seen in Figure 6, the separation of the generator at bus 38 results in two stable islands, thus mitigating the imminent instability.

III. EVENT DETECTION, LOCALIZATION AND CLASSIFICATION

One of the futuristic capabilities of the WAMPAC platform is how to achieve a high degree of situational awareness and reliable electricity grid operation. In particular, the development of real-time detection, localization and classification (DLC) of disturbance events is gaining attention in the scientific community since it directly strengthens the centralized control capabilities under vulnerable grid conditions. With the advanced sensory and communication protocols evolving under IEC61850 SV and IEEE C37.118.2 standards, achieving real-time (RT) data acquisition is a stepping stone for the development of real-time DLC algorithms.

Despite successful DLC algorithms (based upon signal processing and statistical AI classification domains in terms of efficiency), adaptability and scalability are matters that deserve attention. With the advancements of big data analytics, fast processing of a vast volume of streaming sensory data through machine learning (ML) and deep learning (DL) algorithms is gaining interest [16,17]. Although, AI-based DLC tasks can be seen as a topic under situational awareness, for RT studies each task has unique characteristics. Figure 8 depicts a block diagram of a laboratory-scale deployment of an RT DLC expert system on a WAMPAC platform.

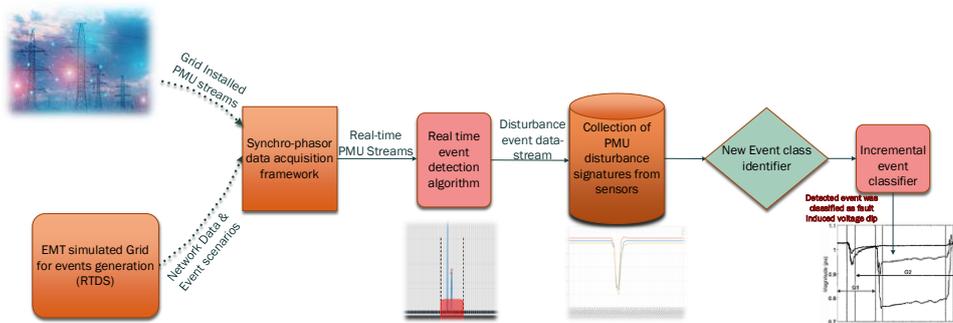


Figure 8. An expert system comprising Real-time disturbance event detection, classification and localization.

It can be divided into several stages: RT event generation, RT event detection, event localization, feature extraction, and incremental event classification stage. For RT events generation, the RTDS-RSCAD platform is chosen for its RT operational capabilities and for its aptness to produce synthetic streaming data close to real life. The Synchrophasor Application Development Framework platform [15], as explained in Section II, acquires time-sampled PMU streams mimicking a real-life cyber-physical data acquisition platform. RT event detection algorithms act as the first line of defence that is deployed online for continuous operation. These algorithms have to unceasingly screen a large volume of sensory streams for detecting disturbance anomalies. Discriminating and handling false alarms from disturbance event triggers is becoming increasingly challenging considering temporal and seasonal drift in sensor data due to RES penetration. Also, with the increase in input streams, the algorithm should be sufficiently scalable [18]. Hence, scalable, automatic sensitivity-adaptable, online-operational ML algorithms which can capture the underlying dynamic nature of the grid are preferred. With the events detected, the next stage involves achieving a reduced number of discriminant features with minimal processing. This pre-processing stage extensively improves the later event classification, however, at the cost of the computational burden. With presently available parallel-computing capabilities, this feature extraction and event localization tasks have been greatly benefitted. Lastly, the RT event classification or recognition stage unlike the RT event detection stage is not prone to device scalability, however, functional scalability of the classification algorithm is a challenging task with a growing set of new events. Just like the human thought process, the algorithm should be able to first recognize and discriminate a disturbance event as a new event class or an event from a pre-trained event class. This part is considered as an assumption in most of the disturbance event classification literature [19,20].

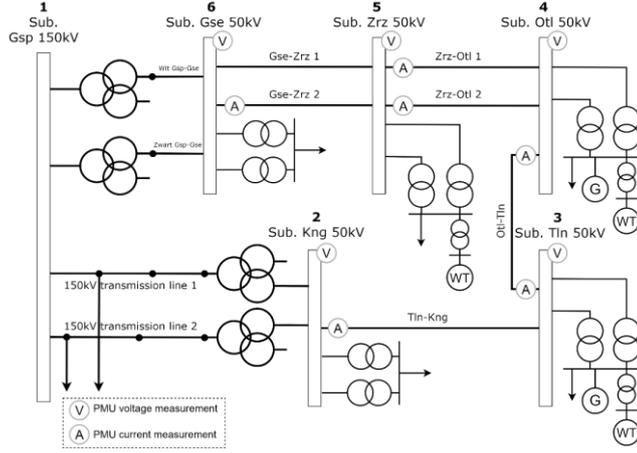


Figure 9. The schematic of the Stedin MV grid and the PMU measurement

Both supervised and unsupervised classification algorithms require the event classes and the number of event classes predefined respectively. However, new event classes are expected to be introduced by varying grid operation modes. Thereby, a new disturbance event identification algorithm creates/updates the class label accordingly. With this input, a supervised incremental deep learning classification algorithm classifies the event class. Furthermore, based on classification confidence, incremental training and adaptation are instantiated. Figure 9 depicts an actual 50 kV ring of a Stedin network located in the southwest of the Netherlands. This benchmark grid is used to generate live PMU streaming data of normal as well as disturbance events. All PMUs are installed in the 50 kV network.

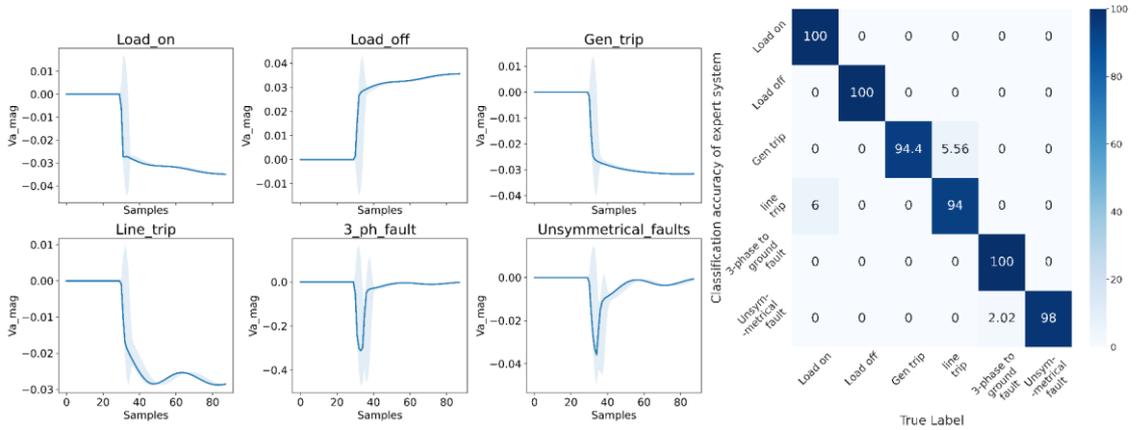


Figure 10. (a) Disturbance Events after pre-processing stage. (b) Incremental Learning accuracy after classification stage

Figure 10a shows the pre-processed disturbance events captured at the event collection stage. The events are generated and fed to the classifier in an incremental fashion compelling the DL algorithm to operate on the fly. Six types of events, namely sudden load variations, generator trip, line trip, symmetrical and asymmetrical faults are instantiated randomly and fed to the RT DLC expert system for classification. The average classification accuracy is 97.73% (see diagonal of the heatmap in Figure 10b), and it is achieved by the real-time DLC expert system illustrated in Figure 8. The classification algorithm updates at each stage when a new set of disturbance events are encountered.

IV. REAL-TIME POWER SYSTEMS VULNERABILITY ANALYSIS

Power systems vulnerability can be defined as a risk level with respect to the occurrence of cascading events. The vulnerability analysis is therefore aiming to monitor, quantify, and ultimately help avoid catastrophic blackouts. It comprises several on- and off-line methods, of which two are of utmost importance, as highlighted in Figure 11.

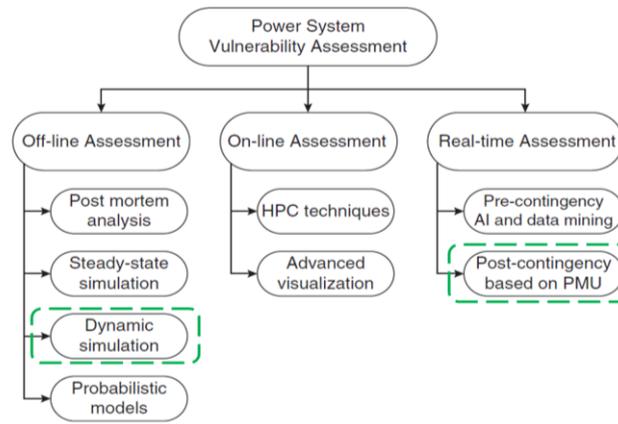


Figure 11. Vulnerability assessment and the focus within the project (adapted from [21])

The introduction of advanced PMU-based Energy Management Systems (EMS) discussed in section I enables a novel post-contingency real-time vulnerability assessment. As resilient system operation becomes more challenging, the Dutch electricity grid operators improve the real-time observability by making use of PMUs on not only transmission but also distribution level [22]. This makes the grid suitable for testing and applications of advanced vulnerability assessment solutions. Meanwhile, the complexity of power systems is rapidly increasing on all voltage levels. As more distributed energy resources (DER) and dynamic loads emerge on medium- and low-voltage levels, their aggregated effects on a power system become significant. It is therefore important to monitor and analyse system vulnerability at the intersection of distribution and transmission systems, to prevent risks of cascading faults. The first step is understanding the new phenomena via dynamic simulations, which utilize advanced modelling techniques. By applying detailed dynamic simulations, it is possible to better understand the increasingly complex system response as highlighted in Figure 11 and explored in [23]. The experience shows that the risk of post-fault rapid cascading notably increases with the proliferation of DER and the dynamic loads. The risk of such cascading is exemplified and visualized in Figure 12. The interactions occur in a short (<10 seconds) timeframe.

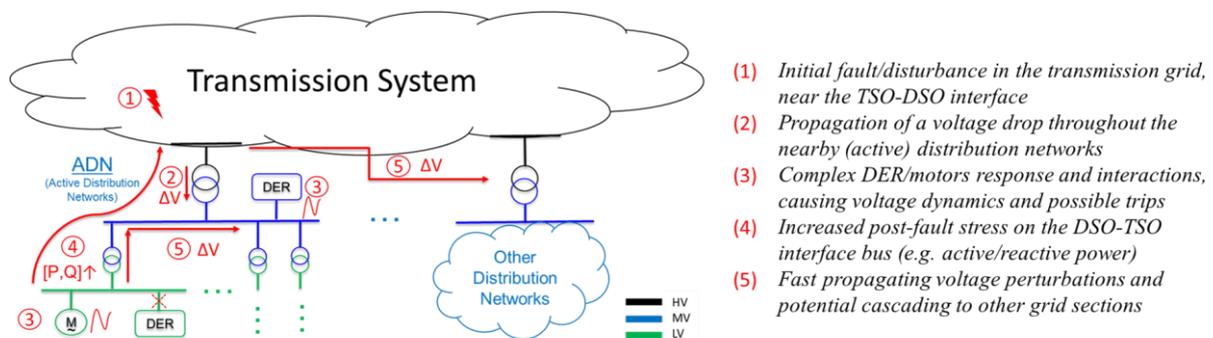


Figure 12. Exemplified impact of Active Distribution Networks (ADN) on the post-fault resilience

Such a chain of events may present resilience concerns for the grid, exposing it to vulnerability challenges and chances of cascading disturbances. The concerns are more emphasized with the accelerated increased level of renewable energy integration. For higher voltage levels, especially in the areas with massive use of Inverter-based Resources (IBR), some of the most important challenges are directly related to the decommissioning of synchronous generation (SG), which has acted as a backbone in the power systems. With their rapid reduction, power systems face many technical challenges. As mentioned earlier, with lower system inertia, system frequency is more affected by sudden contingencies resulting in instabilities. However, in parallel to such effects, the reduction of synchronous generation also leads to the reduction of system strength, which is strongly correlated to voltage stability problems. Figure 13 visualizes the relation of these effects.

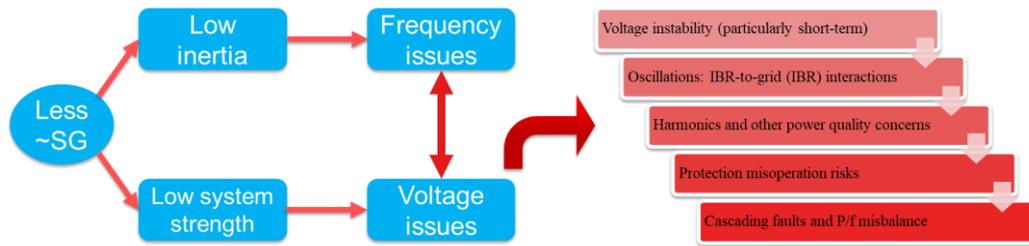


Figure 13. Fundamental system impacts due to the reduction of synchronous generation

It is important to acknowledge that even when a grid as a whole is resilient and strong, large IBR indeed is often concentrated in certain grid areas leading to local vulnerability, often resulting in voltage-related problems. IBRs effectively act as a sink to system strength, and as their penetration locally increases with respect to the amount of synchronous generation, the grid essentially becomes weaker and less resilient to voltage perturbations. This may lead to short-term (voltage) instabilities [23].

In terms of coping with the presented technical challenges imposed by IBR and DER proliferation throughout the power systems, a couple of key directions are needed. A more detailed evaluation of active distribution network responses [23] helps identify the most important factors that may initiate or aggravate vulnerability concerns. The goal is to be able to pinpoint buses and grid sections exposed to a larger risk and quantify them so that suitable preventive measures can be taken. Moreover, collecting PMU data, on both transmission and distribution levels, can help to monitor and detect dangerous grid dynamics in real-time as they occur [22], as well as to apply novel algorithms to quantify vulnerability induced by the observed disturbances and dynamic responses. On the IBR-to-grid interface, system strength plays a major role in determining whether a certain disturbance may lead to dangerous risks of cascading. Innovation in how we quantify the resilience in IBR-rich areas is a necessary step toward evaluating system vulnerability. This further enables the utilization of PMU/WAMS measurements to detect short-term instabilities and oscillations in weak points in the grid. In that regard, it is shown that the existing methods are largely unsuitable and ineffective in modern power systems [24]. The limitations are analysed further, opening opportunities for future novel detection algorithm solutions.

V. CONCLUSIONS

To meet the requirements of having a highly reliable, secure, and sustainable electrical power system, one of the major challenges is how to detect and eliminate disturbances that may lead to severe outages. The utilization of synchrophasors plays an important role in monitoring and collecting big data, which on one side can be used to run coordinated algorithms capable of performing corrective measures. On another side, collected big data can be used for data analytics and AI-based algorithms to recognize and classify severe disturbances. These types of applications can help to increase system resilience by timely detecting different anomalies in the power systems. In return, this may allow an even higher share of renewable energy integration. In the future, as an application of situational awareness, a real-time expert system will be deployed, in which PMU streams collected from transmission and distribution grids should be used for designing and automatically calibrating AI-based methods. The detection algorithm will be trained to recognize more complex power quality events and disturbances so that the expert system can adaptively learn the new disturbance events on the fly.

VI. ACKNOWLEDGEMENT

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