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Abstract

This paper deals with the essentials of synchrophasor's applications for future power systems to increase system reliability and resilience, which have been investigated within a four-year research project. The project has several applications, covering real-time disturbance detection and blackout prevention distributed across multiple work-packages. Firstly, an advanced big-data management platform built in a real-time digital simulation (RTDS) environment is described to support measurement data collection, processing, and sharing among stakeholders. This platform further presents and demonstrates a network-splitting methodology to avoid cascading failures. Online generator coherency identification is another synchrophasor application implemented on the platform, the use of which is demonstrated in the context of controlled network splitting. Using synchrophasors, data-analytics techniques can also identify and classify disturbances in real time with minor human intervention. Therefore, a novel centralized artificial intelligence (AI) based expert system is outlined to detect and classify critical events. Finally, the paper elaborates on developing advanced system resilience metrics for real-time vulnerability assessment of power systems with a high penetration of renewable energy, focusing on increasingly relevant dynamic interactions and system instability risks.

2012 ACM Subject Classification Hardware → Power and energy; Theory of computation → Design and analysis of algorithms

Keywords and phrases Grid Resilience, Synchrophasors, Real-time Cyber-Physical Experimental Testbed, Real-Time Monitoring, Protection, and Control, Event Detection Classification, Artificial Intelligence, Adaptive Incremental Learning, Controlled Islanding, Vulnerability, State Estimation, Dynamic Line and Cable Rating

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1 Introduction

Electrical Power Systems (EPSs) undergo significant changes which result from the high penetration of renewable resources. The increased amount of renewable energy shows a negative impact on system inertia and strength. Additionally, using more power electronics causes reduced and bi-directional fault currents, which are difficult to detect. Another significant aspect is the continuous aging of the equipment (especially cables), which may sometimes fail due to old insulation and cause unwanted tripping of the power system protection (e.g. Amsterdam blackout, dated January 17, 2017). All these matters raise questions: Will the existing monitoring, protection, and control schemes be sufficient to cope with new system dynamics imposed by intermittent renewable resources? How can the system be more secure and more resilient to new phenomena (low fault currents, inertia, harmonics, power swings, and protection maloperation)? These questions are crucial for system operators, transmission and distribution utilities, as well as suppliers of power equipment. The ongoing energy transition requires establishing new platforms for monitoring, protection, and control, which will be essential to increase the reliability and security of supply. This is the main goal of this research project, supported by a broad consortium of industrial partners.

Synchronized measurement technology (SMT) utilizes Phasor Measurement Units (PMU) [22] to deliver time-synchronized wide-area measurements near real-time. The SMT is the key building block of the Wide Area Monitoring, Protection, Automation and Control (WAMPAC) system [27, 32], which can improve system security, stability, and reliability. The conventional PMU measurements are obtained at 50/60 frames per second, which provides EPS dynamic behavior observability within the 10 Hz range. Additionally, point-on-wave measurements enabled by powerful SAS sensors technology available in the Netherlands can observe frequencies of up to 4 kHz [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 on decision-making algorithms depending on the types of disturbance. IEEE Std 1159 [2] defines and summarizes classification methods, and IEC 61000-4-30 [33] defines classes of disturbances. These standards define the classification based on the waveform characteristics (like switching overvoltage, fault current, and voltage dips). The key contributions of this project are: i) a novel synchronized data management platform is presented, which collects measurements in real time with advanced post-processing techniques. The purpose of this platform is to host integrated novel protection and control schemes and other applications derived from real-time updated datasets. ii) A new out-of-step protection algorithm based on real-time synchrophasor measurement data has been developed and compared to existing solutions. The new solution is shown to be more effective and faster than the existing solutions, realized by using the latest General Electric equipment. iii) Developing artificial intelligence models based on incremental learning to detect and classify specific disturbances. These models can be applied to detect anomalies that may arise in the power system due to equipment aging and, in this way, to prevent sudden component failure. iv) Finally, short-term voltage stability and grid vulnerability assessment in the transmission and distribution grids have been investigated to evaluate system strength and the risk of cascading in order to prevent system voltage collapse.

The paper is organized as follows: Section II provides a general overview of the problem and the methodology of its solution. This section also demonstrates the potential application perspective and elaborates on developed concepts. Section III briefly elaborates on the project consortium structure and the individual contributions of its members. Section IV deals with the key results and addresses each project work package separately. In this way, the new platform is shown to enable the detection of both electromechanical and electromagnetic disturbances. Finally, the paper ends by describing the future possible steps and prospects.

2 Project description and motivation

The ReSident[1] project is motivated by the challenges of controlling future electric power grids, such as reduced system resilience and increased operational uncertainty due to the large-scale integration of renewable energy sources. By using advanced tools and algorithms and a comprehensive real-time Energy Management System (EMS), the classification of disturbances and assessment of their impact is aimed to be realized to take preventive operating actions and real-time remedial actions for anticipating and preventing significant system failures. The visualized overview of the ReSident project is given in Figure 1.

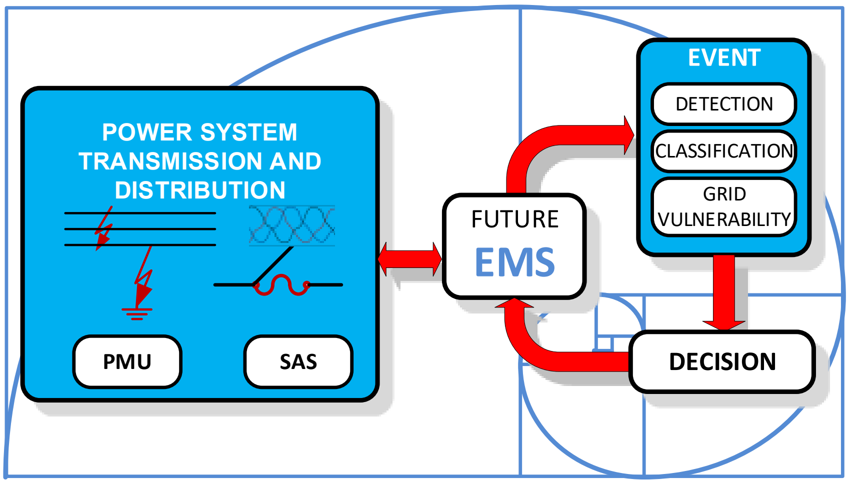

Figure 1 Resident project overview.

The research scope of the Resident project consists of four work packages (WPs). The WPs share a common goal of addressing the resilience of modern power systems from various perspectives. This is highlighted in Figure 1, including the illustrated relation between different tasks. The four WPs and their respective research objectives are listed below.

- ***WP1–Next-generation Energy Management System (EMS) Platform:*** The first work package sets up the cyber-physical experimental test bed. It deals with creating a real-time communication platform for the simulation of power systems based on real-time data, as well as testing and validating WAMPAC applications. Upgrading the SCADA-based telecommunication system with SMT enables greater observability and enhances real-time contingency analysis capabilities. The first step is to estimate the system states (nodal voltage magnitudes and angles) and achieve high real-time grid

[1] Resilient Synchromeasurement-based Grid Protection Platform.

observability. Vast knowledge of network topology, breakers status information, line/cable impedances, and other parameters previously collected for offline load flows are used to create a model-based real-time situational awareness platform. Furthermore, this platform is enhanced by the additional measurements received by the online dynamic line rating (DLR) tool, which manages network congestion that arises due to a highly intermittent RES-dominated power grid.

- ***WP2–Event Detection, Localization and Classification:***
  This work package continues on WP1 and focuses on developing WAMPAC applications that improve real-time situational awareness and perform online pre-contingency analysis. In this context, the first task is to identify disturbances and locate the sub-areas and components responsible for these disturbance events. The second task deals with data-mining to check when the event has been foreseen. Third, when the event has already been foreseen, the event type is classified in real-time. Fourth, when the event is novel and arises from newly installed technologies, dynamic incremental learning is used to update the AI model in near-real time. This ensures an AI-based event classification model adapting through grid transition, supporting network operators with a pre-contingency analysis.
- ***WP3–Stability-aware Controlled Network Separation:***
  This work package focuses on deriving methods for the early detection and prevention of out-of-step (OOS) system conditions. This is facilitated by using wide-area measurement information and developing a controlled system separation and re-stabilization scheme. The first task is to tackle controlled network separation, and instability has to be recognized. After a disturbance occurs, the risk for loss of system stability is monitored concerning several machine-related and system-wide stability indices, and coherent generator groups are identified. The optimal splitting cutsets and control actions are developed and tested on the WP1 experimental test bed, based on which the controlled network separation is executed. Additionally, advanced OOS protection schemes are developed, comprehensively tested, and implemented in the field.
- ***WP4–Grid Vulnerability and Cascading Failures Prevention:***
  The last work package deals with developing offline and online algorithms and tools for the vulnerability assessment of modern power grids. An unprecedented evolution occurs in electric power systems due to the integration of massive amounts of renewable generation, leading to novel and complex stability challenges. Concurrently, robust conventional fossil-based generation is phased out, resulting in resilience challenges. Therefore, it becomes increasingly important to understand and accurately evaluate the vulnerability and resilience of modern power systems so that the risk of instabilities occurring (e.g. uncontrolled separation from WP3) can be minimized. This work package aims to develop algorithms to quantify, anticipate, describe, and prevent cascading failures and system collapse risks by utilizing both offline as well as the real-time data platform from WP1.

The detailed work of all four WPs is described further in Section 4.

3 Project consortium structure and cooperation

The consortium of this large project consists of experts with different backgrounds related to transmission and distribution system operation, measurements, and wide area monitoring and protection. TSO TenneT, and DSOs Stedin and Alliander are utilities that facilitated the project by providing significant data for the transmission and distribution grids that were examined and based on which the algorithms were developed and tested. One of the grids that was taken as an example is a distribution grid operated by Stedin, which has been modeled in a real-time digital simulator. As a manufacturer and one of the main suppliers of equipment for Dutch utilities, General Electric (GE) provided equipment and training for the researchers who verified their algorithms by commercial GE Relays. One of the developed applications has also been installed in the Icelandic electrical power system to detect islanding conditions and provide relevant protection. Another application of GE relay was used for hardware-in-the-loop validation of the dynamic line rating tool for real-time ampacity calculations using solar and wind weather data provided by VSL. Furthermore, the consortium significantly contributed to various engaging technical discussions throughout the project duration that helped shape and improve the developed solutions.

4 Key results

This section discusses the key findings from various WAMPAC applications, which can be congregated into three groups based on the challenges addressed. Applications belonging to the first group aim to achieve real-time situational awareness and improve power system dynamic performance in the long run. Typical examples are real-time state estimation for comprehensive EPS observability and real-time dynamic line rating for online identification of network congestion described in WP1. The second group in WP2 forms a set of pre-contingency-related WAMPAC applications for detecting and mitigating disturbances arising from planned or unplanned power system events, such as real-time disturbance detection, localization, and classification. Further, with the increasing interest in data-driven approaches, we discuss the importance of online training in data-based detection and classification models. Online and near-real-time model training improves parametric sensitivity and avoids misclassification due to concept and/or data drift. Finally, in WP3 and WP4, the third group consists of applications tailored for post-contingency to reduce the adverse impact of the events and improve the system restoration through centralized remedial action schemes. Typical examples are controlled islanding and post-event grid vulnerability assessment.

4.1 WP1–Next-generation Energy Management System (EMS) Platform

Power system control paradigms are shifting from the traditional local control schemes to the modern wide-area synchrophasor data-assisted control schemes. The next-generation EMS platform constitutes a collection of computerized workstations responsible for maintaining the stability of inter-operating AC-HVDC-Smartgrid infrastructure. The platform should also guarantee a secure, reliable, and economically efficient energy management system [20]. In this context, the SMT-supported and WAMPAC-ready cyber-physical testbed is developed as shown in Figure 2. This testbed constitutes 4 layers. From the bottom up, the physical system layer runs simulations to characterize power system dynamics. The networked physical component layer models synchrophasor measurement devices, smart meters, and relays that are equipped with telemetry and, simultaneously, interact with the physical system. The communication network emulation layer creates software architecture for the data transfer. The application layer is where to host various synchrophasor applications. The web-based SMT monitoring platform named Synchro-measurement Application Development Framework (SADF) fills the scientific gap between IEEE Std. C37.118.2-2011 specifications and implementation support for the online synchro-measurement data collection. SADF software library, for the first time, enabled online receiving and parsing of the machine-readable format in the MATLAB programming environment in real-time. Also, we highlight that SADF is the first open-source, available implementation for the IEEE Std. C37.118.2-2011 [22]. SADF is extended further with parallel processing architecture instead of serial processing to utilize high reporting-rate streaming PMU data for processing complex, computationally intensive model-based and data-based (AI) algorithms.

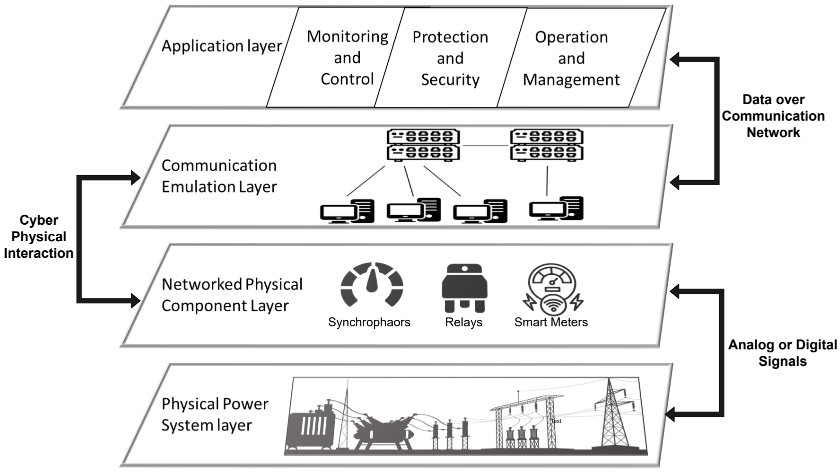

Figure 2 SMT-supported WAMPAC-ready cyber-physical testbed.

As a first application, we utilize our test-bed to realize the true operational state of the grid which is the goal of any TSO or DSO. With streaming time-synchronized PMU data, it is now possible to transit from industrial standard SCADA-powered static state estimation to real-time PMU-based dynamic state estimation [31]. To demonstrate this, a real-time PMU-based state estimation platform for distribution grids is developed, tested, and validated using RTDS. The developed platform serves as proof of concept for potential implementation in an existing 50 kV ring network of the Dutch distribution utility Stedin located in the southwest of the Netherlands (Zeeland province). To catch up with the fast sampling rates of PMUs, the platform incorporates computationally efficient techniques for state estimation. We also incorporate advanced detection, discrimination, and identification of anomalies like bad data (BD) and sudden generation and load changes. Forecasting Aided State Estimation (FASE) has been utilized to enable measurement innovations needed for fast anomaly detection, discrimination, and identification (ADDI), whilst the Extended Kalman Filter (EKF) algorithm is selected to provide fast state forecasting and filtering. The platform has been tested under various normal and abnormal operating conditions considering different statistical properties of sudden load change, measurement noise, and BD scenarios. To demonstrate the advantages and disadvantages of embedding EKF into the platform, EKF is compared with Unscented Kalman Filter (UKF) regarding estimation accuracy, computational efficiency, and compatibility with the module for ADDI. To our knowledge, this was the first validation experiment of the potential implementation of PMU-based real-time state estimation for a real-life distribution grid, achieved through an SMT-supported WAMPAC-ready cyber-physical testbed.

The next WAMPAC application deals with real-time dynamic line rating (RT-DLR). Often, system operators face network congestion issues forcing them to implement preventive or corrective measures, such as generation rescheduling (re-dispatch), with undesirable economic consequences for the system operator [24]. The foreseeable network congestion achieved through state estimation originates from a coincidence of several factors: 1) High reliance on electrical energy has resulted in the increased electrification of residential, transportation, and industrial energy demand, 2) Large costs and difficulties in constructing new overhead transmission lines and underground cabling assets, 3) Significant growth in the share of intermittent Renewable Energy Sources (RES).

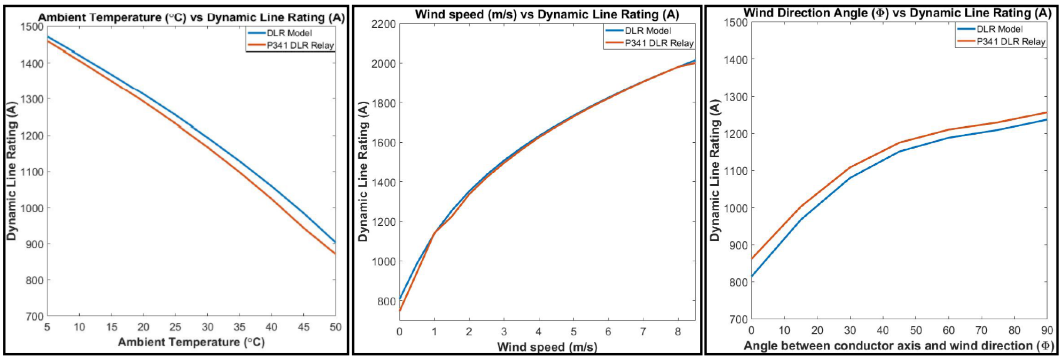

Figure 3 Comparative analysis between RT-DLR and P341 DLR Relay on DLR calculated for the variation in ambient temperature, wind speed, and wind direction.

RT-DLR uses a software-in-the-loop (SIL) test setup consisting of three main parts. The first is the same electrical network utilized by the real-time PMU-based dynamic state estimation, followed by the second part, the weather model. An API is utilized to obtain updated weather parameters, such as ambient temperature, wind speed, and latitude, from the weather stations deployed at the selected location into the MATLAB programming environment. The last part is the resistance and ampacity calculation. The line resistance is calculated using a PMU-based algorithm using bus voltages and branch currents. Considering the weather parameters' influence, a SIL operation by updating the RTDS network is created. The developed DLR model is validated against GE's MicoM Agile P341 DLR relay through a Hardware-in-the-loop setup. Figure 3 describes a comparative analysis between RT-DLR and P341 DLR Relay on ampacity calculated for the variation in ambient temperature, wind speed, and wind direction. It is noted that our RT-DLR-based ampacity calculation method emulates the results of the GE relay under different weather conditions.

4.2 WP2–Disturbance Detection, Localization, Classification, and Learning

With the advanced communication and sensory protocols outlined under IEC61850 SV and IEEE C37.118.2 standards, network operators are subjected to receive streaming high-sampled data in real time. This advancement is raising interest in data-centric models due to: 1) the abundant availability of high-quality data. 2) proven success in parallel disciplines of artificial intelligence. One of the revolutionary features of the WAMPAC platform is its capability to offer a high level of situational awareness and dependable grid operations. To this end, the advancement of real-time detection, localization, classification, and learning (DLCL) of disturbance events draws interest from the scientific community as it improves centralized control and remedial action schemes under decentralized low inertial grid conditions.

The work of disturbance DLCL has four noticeable components. The first component is disturbance detection which picks up any abnormality in the PMU streams deviating from the quasi-steady-state operation. Disturbance detection in steady state conditions is increasingly becoming complex for the following reasons: 1) Reduced inertia due to decommissioning large rotating generators has made power systems vulnerable to small dynamic changes; 2) high-

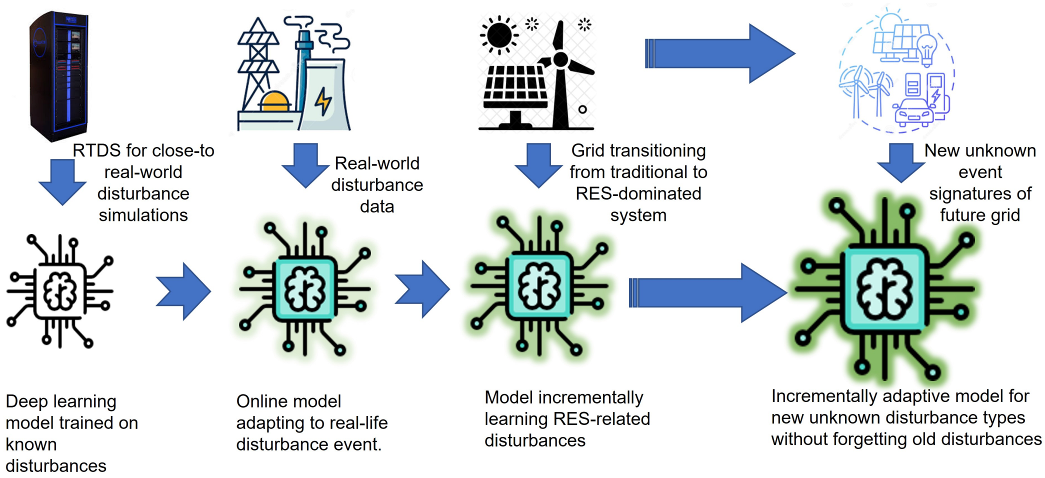

Figure 4 Illustration of an adaptive incremental (AI) model training for disturbance classification.

frequency switching devices in RES and large loads inject harmonics; 3) Multi-dimensional agents controlling the grid operations is incurring sudden generation and load changes. The PMU streams acquired from such sources will be dynamic, noisy, and unpredictable. Further, detecting disturbances upon such PMU streams will be challenging for any non-adaptive statistically-based event detection algorithm [11, 23, 16]. The state-of-the-art has presented many model-based and data-based detection algorithms. Data-based algorithms are gaining more popularity against model-based approaches (digital signal processing and non-adaptive statistical techniques) due to abundant data availability and online training capabilities. These approaches can be analyzed using relative risks and perceived opportunities. In this research, three robust adaptive statistical disturbance detection schemes are developed and analyzed and a data-based real-time adaptive self-learning disturbance detection scheme is proposed [31, 12, 21]. The algorithms are tested under stringent AC and HVDC grid conditions with varying noise, monitoring window length, and several PMU streaming devices.

The second component comprises event localization in a power system. Even though data-based algorithms can identify the PMU devices that are picking up the disturbances, physics-backed model-based approaches based on severity index are more accurate in locating the exact event location. We proposed a method to successfully detect the faulted transmission line, fault type, and the distance to the fault [13]. With our SADF-based RTDS-Matlab co-simulation platform, we developed a PMU-voltage drop-based fault locator, which splits the grid into a user-determined number of subareas based on the PMU locations. Thereafter, an in-depth search is carried out on the faulted area to determine the faulted line. Finally, using a distributed parameter model, fault distance could be determined.

The third and fourth component discusses real-time event classification and learning. The event classification algorithm identifies the event type causing the disturbance signatures. Recent scientific literature has shown great confidence in AI-based classification models, as they can classify events with close to 100% accuracy. Unlike disturbance detection, classification models are not prone to network scalability since only a limited number of IED devices pick up the disturbances at any given time; however, functional scalability of the classification algorithm is a challenging task with a growing set of new event types due to grid transition. Figure 4 envisions training an AI model incrementally for event classification. Just like the human thought process, the algorithm should be able to recognize and discriminate a disturbance event as a new event class or an event from a pre-trained event class. This part considers an assumption in most disturbance event classification literature [30].

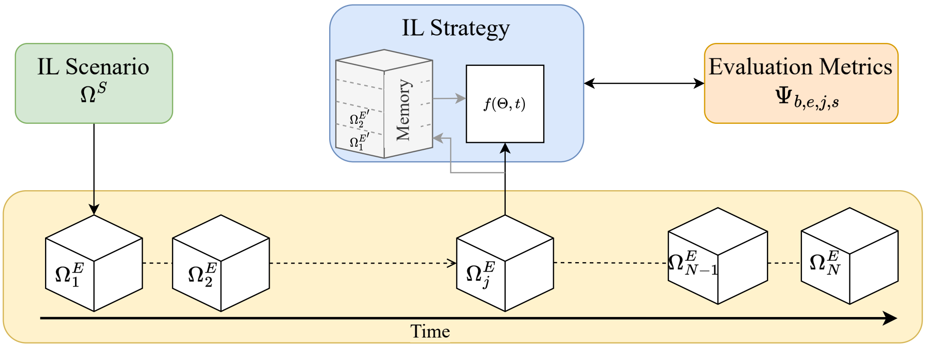

Figure 5 Description of incremental learning strategy - training a deep learning model with new event type scenarios further controlled by evaluation metrics.

Furthermore, if the disturbance encountered is new, the model will be trained incrementally for the new event type on top of the previously trained model. One issue with repeated training of new event types is that the model forgets the intelligence built to remember the previously trained events. This may lead to failure to identify similar disturbances of the same type in the future. This forgetting caused by repeated memory overwriting, is called catastrophic forgetting [18]. The proposed dynamic incremental learning method in Figure 5 addresses this catastrophic forgetting phenomenon to safely update data-based event classification models deployed in future control rooms[30].

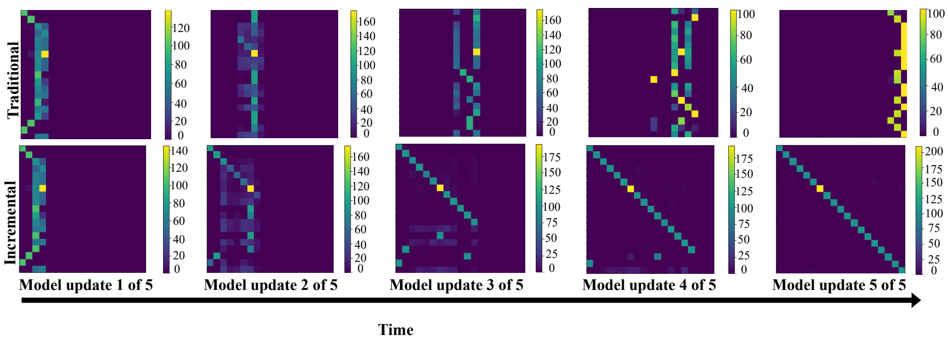

Figure 6 Comparative analysis between online training of deep learning model using a traditional strategy and incremental learning strategy.

By using evolving confusion matrices Figure 6 provides a comparative analysis between online training of deep learning model using traditional and incremental learning strategies. The first row in Figure 6 depicts how a model tends to forget previously trained event types when updated online on the fly. This can be seen from the vertical bands that shift to a new position after each model update. However, in the second row, the strong alignment of the diagonal elements indicates high classification accuracy for each model update. The method is designed to learn efficiently for incoming disturbance data with minimized training time and the highest classification accuracy eliminating catastrophic forgetting. The obtained results show the methodology's performance based on classification accuracy, training time, and storage memory.

4.3 WP3–Stability-aware Controlled Network Separation

Modern interconnected electric power systems (EPS) face significant challenges due to several factors, such as electricity market deregulation, the increased utilization of intermittent renewable energy sources, and aging equipment. As a result of the confluence of these and other factors, there has been a rise in the incidence of severe EPS events and blackouts in recent years [14]. Noteworthy examples of such events include splitting the European power grid in January and July 2021, the 2021 Texas blackouts, and the 2016 South Australian blackout. Generally, large-scale power failures are triggered by an uncontrolled sequence of events that culminate in system instability. Figure 7 provides a schematic representation of a typical blackout timeline [17].

Figure 7 Typical sequence of events in a blackout scenario.

The operating condition of the EPS typically undergoes a gradual decline before experiencing a failure, as depicted by the steady-state progression in Figure 7. This decline is often attributed to an unforeseen triggering event in an otherwise healthy power system. Once the EPS enters a vulnerable state, a single triggering event can lead to instability or prompt rapid cascading outages that culminate in instability and blackout. The controlled system separation approach is intended to counteract this chain of events by detecting instability early and immediately computing the optimal line cutset. By doing so, the unstable region of the EPS is separated while minimizing the loss of load and equipment overloads.

The process of controlled separation involves three main decisions: *when to split*, *where to split*, and *what to do after splitting*. These decisions also represent the different stages of the network splitting algorithm. The *when to split* decision is responsible for identifying stable and unstable transients in the EPS and detecting the key EPS elements that cause instability, as this set of elements may change with time. The *where to split* decision involves choosing the optimal EPS branches to disconnect to isolate the unstable part of the EPS. Finally, the *what to do after splitting* decision involves calculating corrective control actions such as load shedding to stabilize each island formed after splitting in a cost-efficient manner.

The first stage of the controlled separation problem is focused on instability recognition. The scope is limited to detecting loss of synchronism (LoS), the most important instability type requiring system separation. LoS in an EPS typically occurs along the boundaries of coherent generator groups (CGG), which are groups of generators that tend to swing together following a disturbance. CGGs are identified using the novel method defined in [21] or operational experience/measurement-based coherency identification [29]. After disturbance detection, the EPS is monitored concerning several machine-related and system-wide stability indices to track the risk of LoS. When the risk of LoS becomes very high, the system split command is activated, and the most disturbed CGG is separated from the grid. This decision logic of system splitting is summarized in Figure 8.

For each CGG, the control actions to stabilize the islands are continuously recomputed based on recent snapshots of the system state. Finding the optimal control actions is formulated as a linear or non-linear integer program to satisfy more physical power system constraints. However, measurements during intensive power swings cannot easily characterize the network's power balance and loading conditions. Thus, the computational time delay between measurement and control is partly compensated by the duration of power swings

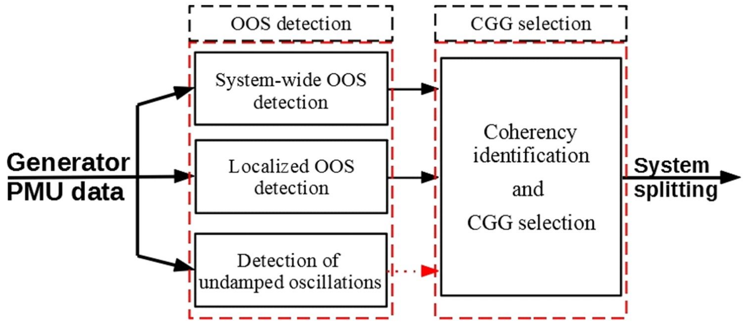

Figure 8 Decision logic of controlled splitting.

before 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. An example of the controlled splitting process is hereby illustrated, based on an IEEE 39 bus network described in [21]. The tripping of an important line causes the generator connected to bus 38 to experience growing oscillations, eventually becoming out-of-step with the rest of the system. This is depicted in Figure 9.In the left part of Figure 9, the top plot illustrates the angles of generator terminal voltages in the system center of inertia (COI) frame of reference denoted as Φ_G^{coi}, and the lower plot shows the corresponding frequencies denoted as f_G^{coi}. Both quantities can be measured in real time by PMUs. The coherency estimation algorithm [28] identifies three CGGs, which include generators located at buses 30–37, 38, and 39, displayed in blue, red, and green, respectively.

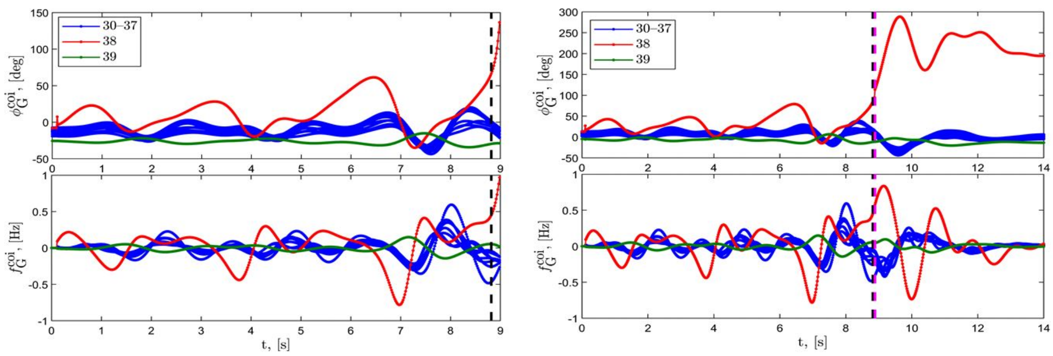

Figure 9 Unstable transient (left) and splitting transient (right).

As depicted in the left part of Figure 9, the generator at bus 38 demonstrates increasing oscillations. Its instability becomes evident 8.7 seconds after the fault inception time, denoted by the black dashed line. The following 0.2 seconds of the sampled transient data verify the instability. Given that the CGG consisting of the generator at bus 38 is the most impacted (displaying the highest average RMS frequency value), it needs to be separated from the rest of the system. The right example of Figure 9 indicates the resulting transient, separating the generator at bus 38 results in two stable islands, thus preventing emerging instability.

Another approach for detecting network instability is to reduce the transmission system into a two-machine system around the observable tie-lines. The impedance of the power network at the terminals of the observed line can be computed by utilizing real-time measurements. After that, using the system impedances, current, and voltage measurements, a power-angle characteristic can be built, and the system's stability can be assessed. This way, an out-of-step (OOS) protection algorithm is developed in a real-time environment [26]. The performance has been compared to the commercially available OOS protection solutions by using RTDS and hardware-in-the-loop methodology. The results confirm that the proposed algorithm detects OOS conditions faster and more reliably than the traditional solutions. However, the reduction of the network has the drawback of requiring a step change to occur in the network to compute the equivalent system impedances. An enhanced algorithm has been developed to overcome this limitation, which is decoupled from power system parameters. The decoupled OOS algorithm utilizes angle difference derivative values to detect instability [26, 25]. The decoupled algorithm has been developed for a hardware platform that receives wide-area measurement system signals.

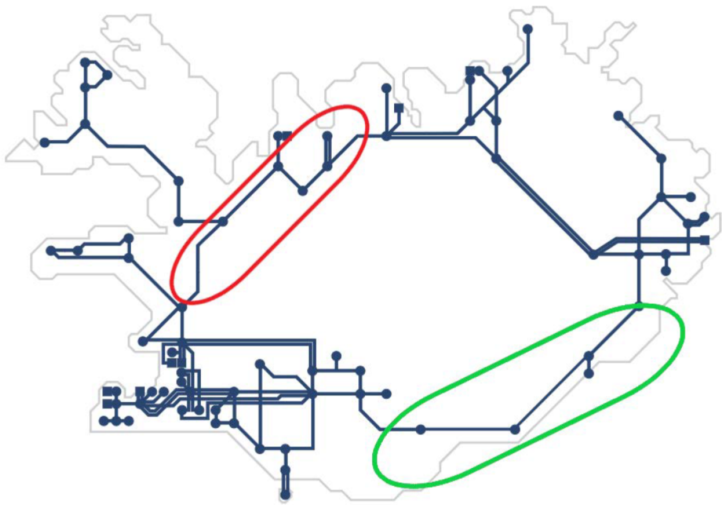

Figure 10 The power system of Iceland, where the newly developed out-of-step algorithm is tested and implemented on the highlighted grid sections.

The performance of the decoupled algorithm has been compared to two existing OOS protection devices available on the market using RTDS hardware-in-the-loop testing, demonstrating faster and more reliable operation. As a result, the decoupled protection algorithm is commissioned and installed in the Icelandic transmission system, illustrated in Figure 10.

4.4 WP4–Grid Vulnerability and Cascading Failures Prevention

In modern power systems that rely on Renewable Energy Sources (RES), technical fundamentals of system operation, security, and resilience are very different from those of conventional power systems. The differences arise primarily due to how RES are integrated into the power system compared to conventional synchronous generators. Synchronous generators (SGs) are massive turbine-powered machines spinning at hundreds to thousands of revolutions per minute. By a carefully designed combination of the rotation speed and spatially distributed energized copper windings, a massive amount of mechanical energy applied by water or steam on the turbine is transformed into electromagnetic force and, ultimately, electrical energy.

At a high level, two main parameters describe the operation of an SG and, consequently, the power system. Those two parameters are *frequency* and *voltage*. The system frequency is proportional to the rotational speed of SGs, in a profound balancing act of supply and demand of active power. When a disturbance occurs, a large amount of rotational kinetic energy stored in the rotating masses is quickly dissipated in a natural attempt to counter the external force attempting to change the state of motion. This is known as *inertia* and is a fundamental concept of conventional power systems. The other aspect of robustness provided by SGs is related to voltage and is a bit more intricate: *system strength*. System strength is a generator's natural ability to counter voltage changes. This effect, however, has nothing to do with rotational mass, but is electromagnetic by nature and is related to the opposition to the change of the magnetic flux between the stator and the rotor of a generator.

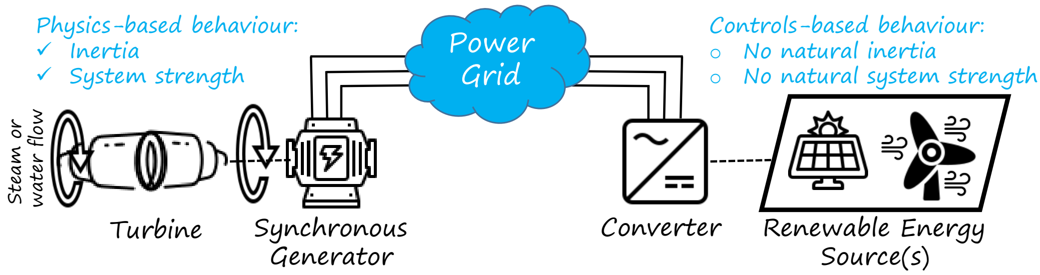

Figure 11 Illustration of some of the fundamental differences between synchronous and inverter-based generation.

Unlike SGs, RES does not have massive rotating machinery with stored kinetic energy or strong electromagnetic coupling to the grid. Instead, they are mechanically and electromagnetically decoupled from the system and are integrated through converters. This means RES, also often referred to as inverter-based resources (IBRs), interact with the system through fast-operating power electronics components, which makes their response more control-based rather than physics-based. Therefore, the behavior of RES is fundamentally different in both steady and (particularly) dynamic state operations, as illustrated in Figure 11.

As the number of RES (SGs) in the grid increases (decreases), the natural resilience of power systems drops. Concurrently, the fast nature of RES controls results in complex dynamics in the grid, which may threaten system stability and increase grid vulnerability. To preserve system resilience, it is necessary to accurately evaluate system strength across both steady and dynamic state operation of power systems [7].

To connect any generation to the grid, one must ensure that the point of connection (PoC) is strong enough for such a connection. This strength is typically evaluated from the perspective of *Short-Circuit Power*, S_{sc} [1]. However, as systems evolve and renewables continuously replace synchronous generation, the concept of S_{sc} loses its significance. To overcome this issue, more accurate methods for system strength evaluation are developed in this project [8]. These more accurately evaluate system strength in the presence of RES and consider other relevant parameters of the grid connection point, such as the operating voltage, shunt elements, and grid impedance. Some of these effects are highlighted in Figure 12.

Besides the steady state operation, the dynamics of power grids are becoming more complex on all voltage levels [15]. A particularly interesting effect is the impact of Distributed Energy Resources (DER), such as solar panels and smaller wind turbines connected to the distribution grid. As the number of DERs rises, the impact on a bulk power system's stability also becomes larger. Furthermore, system demand also becomes more complex, with an increasing number of motors, converter-interfaced loads, and electronic loads.

Extensive studies conducted in [5] reveal how these affect short-term voltage stability and which operating scenarios may lead to vulnerability as the energy transition continues. Some results are illustrated in Figure 13, where the impact of varying penetration of DER and dynamic load on system stability is explored across various parameters.

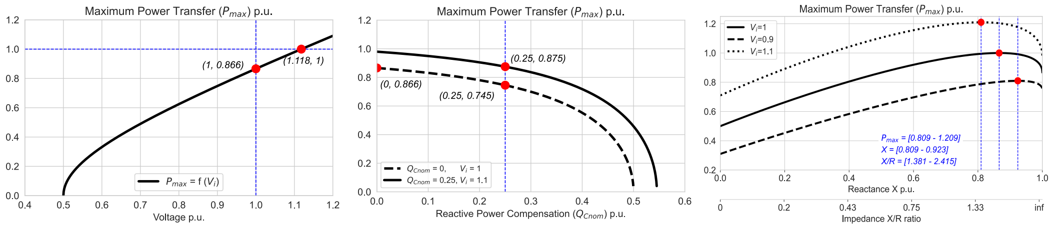

Figure 12 Steady state system strength evaluation in renewable-driven grids with varying parameters: (a) Operating voltage (b) Shunt compensation (c) Varying grid X/R ratio.

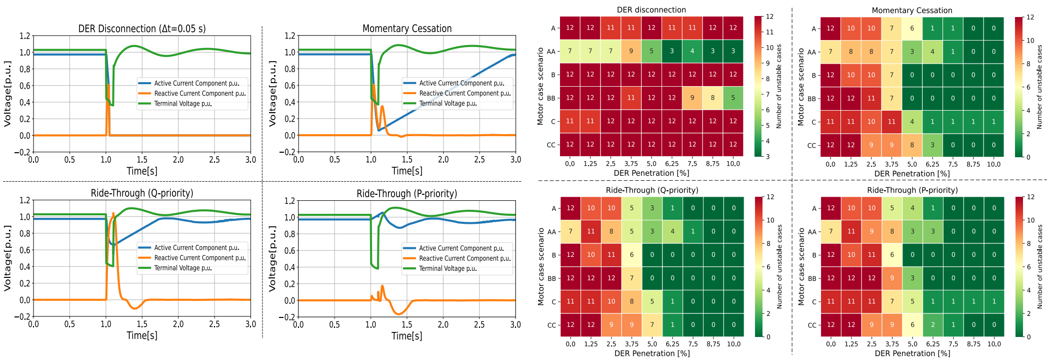

Figure 13 Impact of distributed generation and its controls on grid short-term voltage stability.

As these dynamics and instabilities become more complex, often accompanied by high data uncertainty [19, 3], it becomes increasingly important to utilize and apply advanced data-driven algorithms for stability evaluation [10]. One such algorithm developed within this project is Cumulative Voltage Deviation (CVD) [6, 9], illustrated in Figure 14. The method is designed to automatically utilize either offline simulation data or online measurement data to quantify voltage deviations of various origins. Such an analysis provides dynamic a severity evaluation of potential system disturbances, allowing system operators to proactively react to elevated resilience risks and prevent the occurrence of dangerous cascading faults.

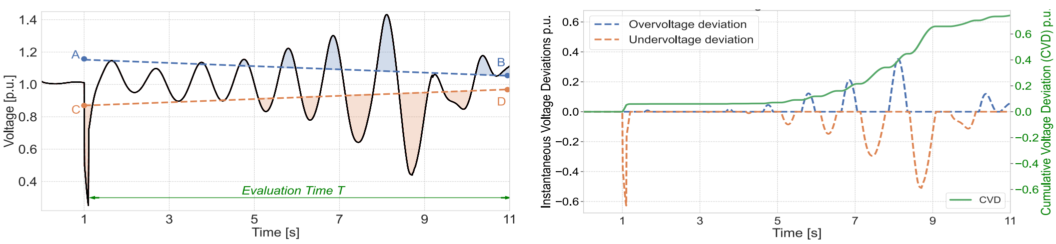

Figure 14 Visualization of the data-based CVD method for quantifying short-term instabilities.

As the resilience of electric power systems decreases, vulnerability analysis becomes crucial. Energy transition reduces inertia and system strength. As a result, faster, intertwined, and more dangerous dynamic phenomena appear. To maintain resilience, evaluation methods also need to evolve. System limitations must be better understood in steady and dynamic states to ensure strength and resilience. As the renewable trends continue, resilience is no longer abundant; instead, it must be (pro)actively provided. Methods developed in this project present a step forward to a more accurate data-based evaluation of system resilience, providing system operators with more information about potential vulnerabilities that pose instability risks and may require operational actions, grid reinforcements, or advanced ancillary services.

5 Further steps and prospects

The Resident project addressed some of the most significant and critical WAMPAC applications for operating modern and future power systems in a more secure and resilient manner. The following prospects are based on our experience with reliable implementation of these applications in future control rooms. A large amount of data availability will require comprehensive hardware to store, analyze and develop models. This means a dedicated workforce of data experts needs to be assigned to TSO's and DSO's who can bridge the gap between data science and vital supervisory planning, operation, and control.

Robust architectural frameworks must be designed to handle applications operating at different time frames. The frameworks should be able to accommodate models that prioritize different performance metrics, such as computational efficiency, accuracy, and memory usage. With the world adapting to data-centric systems for less critical tasks, power system experts and stakeholders should analyze and strategically adapt to changing times. One safe approach is adapting data-centric systems to less critical tasks in network operations, where the stakes of error are lower. Flexible "human-in-the-loop" approaches can be investigated for additional validation of AI-based models. With enough confidence and expertise, hybrid or semi-empirical models can be interwoven with critical workflows such as state estimation, load-flow dispatch, and automatic switching operations corresponding to centralized remedial action schemes. As systems become weaker, they also become more controllable. Using advanced control algorithms and ancillary services to steer systems away from instabilities in real-time across various time scales is a promising field for further research and development.

Additional developments and realization of state-of-the-art tools and algorithms in control rooms and advanced energy management systems are needed to ensure resilient electric power grids. As future power systems must rely on power electronics and increasingly control-driven rather than physics-driven behavior, the additional disturbances and interactions resulting from the interconnection of AC-HVDC electrical grids will inevitably appear more frequently. To cope with these, applying novel real-time synchrophasor-based control and protection schemes will become a necessity for the stable and resilient operation of future power systems.

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