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Spatio-temporal Data-Driven and Machine Learning based Applications for Transmission Systems

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Abstract— **This paper summarizes recent advancements on spatio-temporal data-driven and machine learning methods for static and dynamic security assessment, and their particular use cases. It is a collective effort of different research groups members of the IEEE Working Group on Big Data Analytics for Transmission Systems, to provide transmission system operators (TSOs) with innovative tools and ideas for their potential implementation. The algorithms presented here are classified as non-training and training approaches, namely spatio-temporal and machine learning based, considering as input time series from time domain simulations, and or synchrophasor data from wide-area monitoring systems. The efficacy of these algorithms is then evaluated in different IEEE benchmark models and using real system measurements from different countries.**

Keywords—data-driven, machine learning, static and dynamic security assessment, transient stability, event detection, preventive control, coherency, modal analysis, parameter identification

I. INTRODUCTION

Data-driven and machine learning methods for power system monitoring are key to understand unwanted dynamic interactions in the grid, especially when dynamic models are not available or inadequate to capture the real-world behavior. Moreover, the computational time needed to simulate model-based approaches plays a key factor in utility decision making. Data-driven methods can analyze the data collected within Wide-Area Monitoring Systems (WAMS) from phasor measurement units (PMUs). These methods are particularly promising to identify the dynamics of the current system from these measurements and to predict dynamic stability as dynamic oscillations can be dangerous for stability. Linear signal processing techniques can identify modal information and the current system behavior via linear ringdown analysis. Beyond linear system analysis, the Koopman mode decomposition analyses nonlinear modes and dictionary analysis considers possible dynamic basis functions. Unsupervised learning can identify from the observed data the coherency across generators to identify the generators that respond dynamically similarly. Supervised machine learning (ML) methods are even more promising for applications around near-real-time dynamic security assessment (DSA) and security assessment (SA) as they produce instantaneously the security label, often based on convolutional neural networks (CNNs). Such ML-based SA workflows are promising for low-inertia systems as the timeframes of dynamic events are shorter and the security boundaries may become easier separable with ML. To reduce the computational times of ML-workflows further, feature extraction and dimensional reductions have been explored. Beyond security assessment, ML methods can also be used for preventive control and event detection. The total transfer capability can be predicted for preventive operational planning, and deep reinforcement learning can quickly and sequentially decide under emergencies. Additionally, analyzing the spectrum from synchrophasor data, then using the dynamic wavelet transform can be combined with CNN-based classification to detect (and classify) an event. In [1], several applications of data-driven approaches were developed ranging from python toolboxes and web-based applications for ring down analysis, coherency identification and the identification of dynamical parameters over the analysis on real-power systems such as on the Mexican, USA, Chilean, Brazilian, Ecuadorian, Japanese and Swedish systems. The applications range from static SA with stratified cross-validations and estimating the global operating system state over predicting the time-domain trajectories and assessing the transient stability in real-time, then detecting events, and evaluating real-time synchrophasor data, subsequently, the preventive and secure control with hybrid deep learning. Within these applications, the use of ML is demonstrated on the IEEE Klein-Rogers-Kundur (KRK) System and the IEEE 14, 39, 68, and 140 bus systems. Measurements of real power systems were also used. The following sections, summarize the content of the overall report [1], which due to space limitations, only representative figures of few sections are displayed. The reader is encouraged to read the full report for detailed information on each section.

II. SPATIO-TEMPORAL DATA-DRIVEN METHODS

A. Linear Ringdown Methods for Identification of Oscillations

There are several mathematical methods to extract oscillations when monitoring power systems. Three of the most widely known techniques are Prony, Eigensystem Realization Algorithm (ERA) and Matrix Pencil (MP) [2]. The proposed python-based open-source tool is based on these techniques and works with single or multiple signals. The developed tool is capable of extracting modal patterns from PMU signals which are to be provided in *.csv or *.xlsx format. The tool works in real-time and offline mode. The tool can also tune controllers and provide reduced order models. After the previous techniques are applied to time series, the tool can estimate modes, damping, modal energy, amplitude, and residues. Fig. 1. shows the effectiveness of the developed tool on an illustrative application using a real measured event from the Mexican power system.

B. Koopman Mode Decomposition (KMD) for the Identification of Oscillatory Characteristics

KMD is a relatively novel method for time-series analysis based on the spectral properties of the Koopman operator, defined for an underlying nonlinear dynamical system [3]. The discrete time representation of dynamical systems does not often show up in physical systems, but we can represent continuous time systems like power systems, for instance, through discrete time sampling. The Koopman operator, is a linear, infinite-dimensional operator and its decomposition

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allows to extract Koopman eigenvalues characterized by the time evolution of the underlying dynamical system, allowing to determine an oscillation frequency, and so-called coherency. The linearity of the Koopman operator, under certain conditions, enables us to analyze data with complex behaviors using numerical linear algebra. This approach was applied to the time-series data measured in Japan and as result, the dominant Koopman eigenvalues and Koopman modes were accurate identified [1].

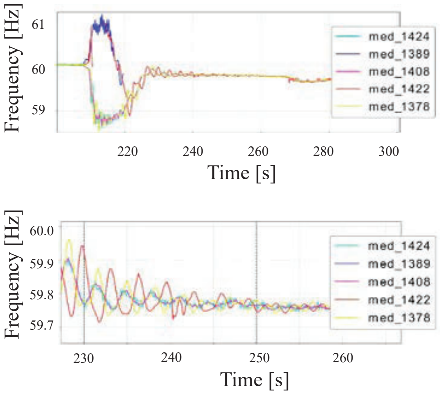

Fig. 1 Actual frequency measurements (top) and ringdown window analysis (bottom)

C. *Clustering Methods for Synchrophasor Data for Coherency Identification*

Clustering is an unsupervised learning task used to perform exploratory data analysis. In the context of power systems, different tasks require clustering such as coherency identification, islanding detection, generate prototypes, and reduction of high dimensional data. To this end, an effort to provide an easy-to-use python-based interface, allowing power systems experts to take advantage of big data by applying cluster-based analysis was developed, which is referred as Clustering Analytics for Power Systems Dynamics or CAPSD [4]. This tool includes some of the most widely known clustering approaches such as K-Means, Hierarchical Agglomerative Clustering Algorithm (HACA), Affinity Propagation (AP), and Typicality Data Analysis. The web front-end interface CAPSD allows the users to apply and evaluate multiple clustering methods. In the report, the results of applying this tool to the IEEE Klein-Rogers-Kundur (KRK) and signals measured from the Eastern Interconnection (EI) power grid in the United States of America are presented. Different examples on how to use the tool for the end-user are provided.

D. *Web-Based Parameter Identification of Reduced-Order Models for Estimation of Frequency Variations*

Data-driven or mixed-type models are becoming more useful, as they can be easily integrated into power system control rooms. Most real-time applications for model identification currently in operation focus on estimating inertia, neglecting the estimation of other parameters. The proposed methodology [5], processes first the frequency in real time measured from a PMU network to capture abnormal frequency variations associated with the sudden changes in power balance. Then, a parameter identification of a reduced order model that mimics the frequency response measured is performed. The tool is implemented in a web application using real measurements of the Chilean power system to show practical significance. On the website, different frequency events in the Chilean power system can be selected from a list. Then, the tool displays the graphic representation of the event and the parameters of the model that have been identified are displayed comparing the actual event against the output of the identified reduced model. The application of this tool could be very useful for numerous applications, for instance, it can significantly reduce the simulation processing time with respect to detailed simulations and opens up the possibility to perform faster than real-time simulations.

E. *Dictionary Analysis of Power System Signal Dynamics*

The adoption of phasor models to represent voltage and current signals from power grids, may no longer be valid in systems with large portions of converter-based generation and decreasing inertia. These systems are likely to see more frequent and extreme dynamic behavior reflected in the measured voltage and current waveforms (e.g., frequency ramps, severe amplitude and/or phase modulations). Such signal dynamics have a broadband frequency spectrum which cannot be captured by the quasi-stationary and narrowband phasor models. Consequently, phasor-based analysis of measurements from low-inertia power systems voltage and current signals can yield invalid parameter estimations and inappropriate control actions. In this regard, a technique to fully characterize common signal dynamics in power grids is proposed and referred as the Functional Basis Analysis (FBA), which is based on a more generic model of the power grid signal [6]. Some common signal dynamics that can be included in the general model are amplitude steps, phase steps, amplitude modulations, frequency ramps and phase modulations. To illustrate the superiority of the proposed FBA technique, it was compared against static and dynamic phasor-based methods. The static technique is a 2-point iterative Interpolated DFT (i-IpDFT) algorithm while the Compressed Sensing Taylor-Fourier multifrequency (CSTFM) method was selected as the dynamic phasor technique. Different simulation results, illustrate how the proposed FBA method, in contrast to the other options, can correctly identify and track the step dynamic, yielding relatively small FE and Time-Domain Error (TDE).

F. *Early Warning and Prevention of Aperiodic Small-Signal Rotor Angle Stability Problems*

Traditional approaches for early warning detection rely on offline analysis and are not able to cope with highly fluctuating systems. The proposed scheme in the other hand, focus solely on the early warning and early prevention of aperiodic small-signal rotor angle stability (ASSRA) components of the overall system and in an early prevention method [7]. In this form there is a dependency on large quantity of data provided by PMUs to ultimately allow full observability of the system in the form of a continuous provision of system snapshots that can be analyzed in respect to the mechanism leading to instability. The early warning and prevention method presented here is then capable of providing a real-time assessment of the ASSRA stability margin of individual generators based on snapshots of the current system state. Moreover, performance in real time is achieved by employing simple algebraically derived expressions for the ASSRA stability boundary that allow to deterministically calculate the distance of each generating unit to the calculated boundary. The results of the replay of the events leading to the large-scale blackout in Denmark and Sweden (Fig. 2) show how the availability of real time data together with the appropriate early warning and prevention method could have prevented system instability with only minor interventions.

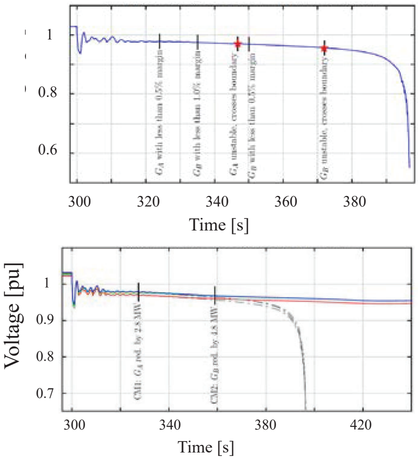

Fig. 2 Early warnings with early prevention deactivated (top). Response with activated early prevention (bottom)

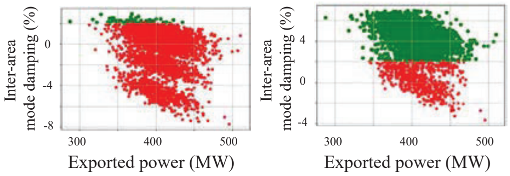

Fig. 3 Inter-Area mode damping vs. Exported power: without PSS tuning (left), with PSS tuning (right)

G. Mean-Variance Mapping Optimization (MVMO) for optimization of WAMS applications.

The complexity of the dynamics of power systems, lead to optimization problems when it comes to dynamic model parameter identification. This process is known to be a discontinuous multimodal and non-convex issue that could not be successfully handled by several of the existing heuristic optimization algorithms, given that their searching performance is sensitive to appropriate parameter settings, which entails a high risk of premature convergence and local stagnation. To overcome these drawbacks, a general time domain parameter identification technique based on the heuristic optimizer Mean-Variance Mapping Optimization MVMO has been proposed for solving several optimization tasks regarding WAMS applications in Ecuador [8]. To give an insight of this work, Fig. 3 shows how the appropriate tuning of a power system stabilizer (PSS), following the proposed MVMO optimization approach for the largest hydroelectric power plant Coca Codo Sinclair (CCS), allows to increase the exports from Ecuador to Colombia, enabling the occurrence of enough number of stable operating scenarios. Similarly, this approach has been successfully implemented for tuning other types of controllers, such as generator speed governors GOV and automatic voltage regulators AVR, to improve the stability of the Ecuadorian power system.

III. MACHINE LEARNING METHODS

A. Convolutional Neural Networks for Static Security Assessment

Static security assessment (SSA) is an important task that focused on the determination of the secure or insecure state of the grid after the loss of a relevant asset. To accomplish this, common operational problems such as overloading of transmission components and violation of bus voltage limits are evaluated under post-contingency conditions through power flow computations. In this form, post-contingency states should be repeatedly evaluated for every prescribed equipment outage under any operating point. Conventional analytical approaches to carry out this task are computationally expensive. The ability of machine learning approaches such as Convolutional Neural Networks (CNNs) to successfully extract features and classify different events, make it a very attractive method for tackling this type of problems and reduce the computational burden. In this form CNN can be effectively used to provide an estimation of the status of the system according to three classifications, namely secure, alarm and insecure [9]. To illustrate the effectiveness of the methodology two applications are presented in [1], the IEEE 39-Bus and the Baja California Sur System (BCSS) from Mexico. For comparison purposes, two traditional ML classifiers, namely Support Vector Machine (SVM) and K-Nearest Neighbour (KNN) were also included in the studies. From the results, it was observed that the proposed CNN model shows a better classification performance [1].

B. Unsupervised Machine Learning to Determine Global Power System Operational State

Different DSA approaches try to offer additional information of instability conditions. This information is valuable for the design of more effective corrective control actions which can include controlled islanding, generator tripping, load shedding, and use of FACTS devices. A proposed DSA model [1], based on unsupervised machine learning (UML) methodology makes the following contributions: (i) a minimum number of features is proposed to determine the security status of the system. This fact facilitates the design and accuracy of support vector machine (SVM) classier. (ii) Euclidean metrics based on the 2D feature space are deduced to estimate the boundary security system, the identification of extreme insecurity contingencies and for estimate the vulnerability degree of the system. (iii) A visualization geographic tool is used to display the situational awareness of the system. The computational burden is reduced due to minimum number of features used during the online application. The IEEE 39-Bus system was used as testbed, where 7 days were selected to simulate the combinatorial nature of power system operations and two extra days (random selection) for performance evaluation of the proposed DSA model. The time domain trajectories of the rotor angular of each contingency were computed and stored. Fig. 4 displays the global trajectories calculated to obtain the feature space for each contingency, where a clustering procedure was used to determine the optimal number of groups. Then, two-security status can be distinguished in Fig. 4, “secure” in green and “insecure” in red.

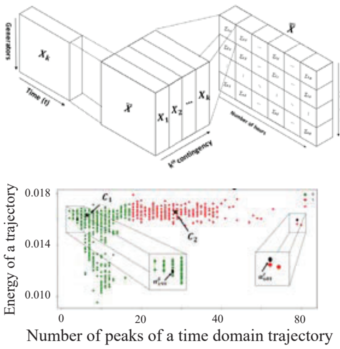

Fig. 4 Tensor storage structure (left) and grouping and classification of N-1 contingencies (right)

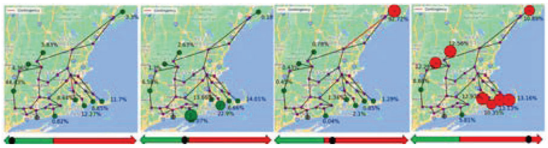

Fig. 5 Operational visualization of the system

Finally, a visualization plot is generated to provide more information to the power system operator. Fig. 5 depicts the operating status of the system for four contingencies with different levels of severity. From this Figure, it can be observed that the visualization tool could be valuable for transmission system operators. The proposed instrument can support on the analysis, planning and design of future maneuvers of electrical power system.

C. *Verifying Machine Learning Conclusions for Securing Low Inertia Systems*

ML-methods were studied extensively for DSA, however, most studies investigated High Inertia (HI) power systems to determine 'the best' ML data, features, and models building upon each other's work for decades. ML-based research for DSA has seldom questioned whether the underlying assumptions for (and the conclusions of) these studies are still valid for Low Inertia (LI) systems. We studied exemplary changes in assumptions (and conclusions) for ML-based DSA when moving from HI to LI systems [10]. The dynamical system of the LI system is brought in perspective with the most typical ML-based approaches, which generally include different sequential steps. The steps consider the generation of the training database, the data pre-processing and feature selection, the model training and validation. Our work analyses each step individually for the changed assumptions in the dynamical LI system, and subsequently, the case study provides a modified test system that corresponds to a LI system and can be used for ML-based research for DSA. The key finding is that using ML is better in LI systems than in HI systems. The LI dynamics are in short timescales which is where the advantage of ML to predict security in milliseconds unfolds. Interestingly, the studies showed that secure/insecure operations can be separated more straightforwardly by an ML in LI systems. Hence, the accuracy increases by up-to 40% toward close to 100% when using neural networks in LI-systems.

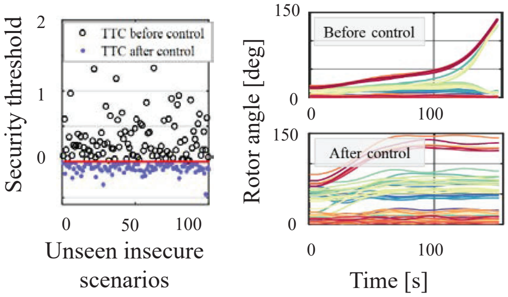

Fig. 6 Online test outcomes of enhanced PPO on unseen insecure scenarios. The red solid line indicates the security threshold

D. *Machine Learning Enabled Preventive Control*

Preventive control aims to ensure the reliable operation of power systems in a future horizon, e.g., the next 15 minutes, by triggering appropriate actions in advance, such as generation redispatch, load shedding, and topology reconfiguration. The preventive control is derived from the optimal power flow (OPF) model with several constraints considering predefined contingencies. Transient stability constrained OPF (TSC-OPF) is one of the most widely used approaches to determine preventive actions with consideration of stability margins in the presence of multiple faults. However, TSC-OPF is computational prohibitive for online preventive control. Very few machine learning models have been used for preventive control in the literature and they are computational demanding for practical applications or only for single-objective optimization without considering the cost and other power systems operational status. In this regard, deep belief network (DBN) is used to identify the mapping relationship between the transient stability index (TSI) and system operational features, total constrained operation planning (TCOP) model is also investigated, whose objective is to minimize the operation costs while meeting several regular constraints and finally, total transfer capability (TTC) security constraints and the generation re-dispatch for TTC control, to operate TTC without violating security constraints are also analyzed [12].

E. *Machine Learning for Online Transient Stability Assessment*

For the problem of transient stability where nonlinear dynamics play a key role, the use of ML based on actual measurements, has been proposed in the literature to overcome limitations by coupling offline time domain simulations with online ML for fast stability assessment. Nowadays, WAMS provide enhanced data in both accuracy and volume, that can inform understanding of potential patterns of instability. In the context of ML for online transient stability assessment (TSA), first an extensive literature review of data driven methods used for this purpose is presented. Then, characteristics such as information on the grouping of unstable generators, examples on how to find and count the number of different instability patterns of generators, decision time and accuracy considerations, estimating indices through regression and interpretability of ML models are widely discussed. Finally, online applications of ML for TSA with an illustrative example of decision regression and rule extraction through interoperability are analyzed [11]. Fig. 6 displays the results of a hybrid deep learning for dynamic total transfer capability control. In this Figure it can be seen that an enhanced proximal policy optimization (PPO) agents enable secure control for unseen scenarios. Interestingly, the proposed method achieves almost 100% accuracy in terms of meeting the desired target control goal for the insecure scenarios generated, thanks to its strong generalizability. The right subplot intuitively shows the angle trajectories transition of one of these successful control cases.

F. Event Detection using Real-Time Synchrophasor Data

One of the key challenges of applications based on WAMS is the correct detecting of disturbances to avoid false alarms during real-time operation as well as offline disturbance analysis. In this work, a two-level robust event detection methodology aiming to reduce false disturbance detection (false positives/alarms) and validating true events is presented [13]. The methodology is divided into stages: first, a signal processing analysis is conducted and then a deep neural network (DNN) classification is performed. In the first stage, a widely known spectral analysis based on Discrete Wavelet Transform (DWT) to event detection is applied and in the second stage, the events detected by the DWT are processed by a DNN to check if it is a real event or a false alarm. The proposed scheme is implemented in a software application based on C# language coupled with OpenECA software, which is responsible for redirecting the received data stream. Real synchrophasor data collected from the Brazilian interconnected power system (BIPS) in real-time is used to validate the effectiveness of the proposed tool. First, DWT preliminary detections of systemic events are performed, which are evaluated by a CNN, with three convolutional layers and two fully connected layers, trained as a binary classifier to validate the detection by reducing false positives.

Online and offline application comparisons show that the accuracy discrepancies between these two applications forms were due to problems with the representativeness of the training dataset.

IV. CONCLUSIONS

This paper summarizes a collection of spatio-temporal data-driven and ML-based approaches for applications on transmission systems that can be fully found in [1]. This document and the report provide system operators with an overview of innovative tools and methods that promise to add value to the growing amount of data and information that operators receive. In [1] the different techniques outlined in the sections of this paper are detailed and it covers applications that provide valorous information about the power system stability conditions. From the wide overview presented in this document, it can be noticed that development of new solutions could open the opportunity to implement advanced tools for the system operators. Those tools, based on data-driven methods and ML strategies can provide additional information about the power system stability condition and provide complementary indexes into the control room, to support the operators to take immediate actions during complex dynamic events. All methods reported here are validated by means of simulations on different IEEE Benchmark models and real systems. Moreover, the characteristics and topology of the different transmission systems are also fully described in an appendix to [1].

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