# On Machine Learning-Based Techniques for Future Sustainable and Resilient Energy Systems

Jiawei Wang, *Member, IEEE,* Pierre Pinson, *Fellow, IEEE,* Spyros Chatzivasileiadis, *Senior Member, IEEE,* Mathaios Panteli, *Senior Member, IEEE,* Goran Strbac, *Member, IEEE,* and Vladimir Terzija, *Fellow, IEEE*

***Abstract*—Permanently increasing penetration of converter interfaced generation and renewable energy sources (RES) in modern electrical power systems makes the power system more vulnerable to low probability and high impact events, such as extreme weather, leading to severe power system contingencies. These contingencies can be further propagated to neighboring energy systems over coupling components and consequently negatively influence the entire multi-energy system (MES) (such as gas, heating and electricity) operation and its resilience. In recent years, machine learning-based techniques (MLBTs) have been intensively applied for solving various power system problems, including system planning, or security and reliability assessment. Their application to MES resilience that can be utilized by coupled approaches across different energy vendors in renewable-rich power systems is, however, still to be fully explored and leveraged for supporting future low-carbon power systems. This paper aims to review and put attention to MES resilience quantification methods of, and the application of MLBTs for supporting the resilience of future sustainable energy systems. The unresolved research questions in the literature on these two aspects are identified and discussed. These future directions can be useful for automatic, effective, precise and fast MES resilience assessment based on MLBTs.**

***Index Terms*—Extreme events, machine learning, multi-energy systems, resilience, sustainable energy systems**

## I. Introduction

DUE to increased number of extreme events, as well as the increased penetration of converter interfaced generation and renewable energy sources (RESs), modern electrical power systems became more vulnerable and technically observed weaker. In other words, without undertaking some preventive/corrective measures, modern power systems will be more fragile to different types of power system perturbations, which could lead to increased number of cascading events and undesirable blackouts. Power systems have been recently experiencing different operational challenges around the globe. For example, the power outage in the UK in August 2019 [1] was initiated by a lightning strike, whereas a severe windstorm in combination with stressed system conditions resulted in a blackout of South Australia in September 2016 [2]. In both cases the impact of RESs played an important role in the severity of the disturbance and the cascading propagation. Such contingencies can be further propagated to other energy vectors (e.g. heating, gas, or transportation) over the system assets coupling independent energy vectors together, such as combined heat and power (CHP) plants, or gas turbines. More recently, the 2021 winter blackout in Texas [3] has clearly highlighted a need for better understanding of the future sustainable energy system resilience, but also actions in developing and applying effective measures to mitigate the impacts of large-scale disturbances. Here the system resilience is directly related to those system events which can be described as low probability and high impact events, e.g. earthquakes, hurricanes, extremely cold weather conditions, or similar. In this context, quantification of the multi-energy system (MES) resilience, where different energy vectors like gas, heating and electricity are mutually coupled, is of utmost importance and is not trivial. Resilience quantification of such a MES should take into account all individual energy vectors' resilience levels and their specific dynamics expressed through time constants describing the speed of their individual dynamic processes.

Machine learning-based techniques (MLBTs) are advanced mathematical tools having the ability of self-learning from measurement data sets obtained from the physical process observed. MLBTs also offer significant number of benefits, compared to traditional and classical approaches, for example: (1) reaching quickly decisions, especially for large-scale non-convex physical models requiring very demanding computational efforts for problem solving, (2) achieving highly accurate decisions, compared to those traditional approaches, e.g. based on model order reduction, or linearisation, (3) utilizing massive historical data sets collected by a large number of sensors described by a high reporting rate, (4) simulation a broad range of scenarios taking into account different sources of uncertainties, (5) forecasting future system conditions, or states, and (6) automatic controlling the grid and ensuring system stable operation in cases of human errors, or delay in human reactions. In the past, MLBTs have been applied to power systems for various purposes, including reliability management [4], system stability assessment and control [5], and contingency analysis [6]. In addition, MLBTs were also used for solving economic dispatch of a MES during normal operation [7]. As known, power system protection is quite a conservative and sensitive discipline relying on strictly robust and traditional approaches. At the same time, it can significantly impact the system resilience level. From one hand, system protection can prevent a move from a normal system state to e.g. extreme one. Similarly, in the context of smart grid technology, smart meters and protective devices can support the system restoration schemes. Resulting from the increased

This work was part of a project which is supported by a research grant (37177) from VILLUM FONDEN. Project title: Data-driven Approaches for enhancing resilience of Multi-Energy systems (DAME).

Work of V.Terzija was supported by Skoltech and The Ministry of Education and Science of Russian Federation, Grant Agreement No 075-10-2021-067, Grant identification code 000000S707521QJX0002.

complexity of some of protection functions, particularly those related to System Integrity Protection Schemes (SIPS), e.g. underfrequency/undervoltage load shedding [8], intentional controlled system islanding [9], [10], or monitoring of power system attributes required by novel and smart technology solutions, approaches based on ultimately data-driven solutions supported by Artificial Intelligence and MLBTs, become the solutions applicable today [11]. However, currently there is a lack of general and in-depth understanding of MLBTs applied to MES resilience assessment and enhancement against extreme events. Furthermore, the integrated resilience services can be leveraged in a MES for withstanding, absorbing and recovering from an extreme event, particularly in situations with high RES penetration.

Therefore, in this paper, the existing quantification methods and MLBTs supporting future sustainable and resilient energy systems will be systematically reviewed. Building on this thorough review, our goal was to investigate and discuss what are the uncovered and important research questions related to 1) the quantification methods of MES resilience, and 2) MLBTs applied to MES resilience assessment. Future directions on these two aspects are further identified to effectively contribute to the whole system resilience assessment agenda in the presence of extreme events, e.g. extreme weather, but in systems with high penetration of RESs, particularly those converter interfaced. Such a review aims to derive condensed and digested conclusions from existing references published in the open literature, and also to propose an outlook for future directions in the field by identifying existing gaps, future needs and feasible solutions.

The rest of this paper is organized as follows. In Section II, literature review on resilience basics, including its definition and other relevant concepts, are presented. The MES resilience modelling and quantification methods are presented in Section III. Literature review on MLBTs applied to MES resilience assessment is discussed in Section IV. Section V is addressing future research direction on MES resilience assessment. Finally, conclusions are summarized in Section VI.

## II. MES Resilience

### A. Power system resilience definition

According to the IEEE Task Force [12], power system resilience is defined as “the system ability to withstand and reduce the magnitude and/or duration of disruptive events, which includes the capability to anticipate, absorb, adapt to, and/or rapidly recover from such an event.” The term *disruptive events* refers to high impact and low probability unexpected perturbation, including extreme natural disasters, or man-made attacks. Typical examples are snow storms, or cyber attacks [13], [14]. With the development of coupling technologies, concepts of digital substation and high speed communication, or distributed power systems, the interdependencies of different energy vectors are stronger than before and the risk of unexpected disruptive, or cascading events is much higher [15]. Doors for propagation of disturbances from one to another energy vector are opened, what is making the case for MES resilience assessment. Therefore, the existing power system related resilience definition is necessary to be extended to MES resilience. This can be done by considering the MES operating states and understanding dynamic processes in individual energy vectors, but also network characteristics of different energy vectors under extreme events.

### B. Conceptual relationship

This paper is focused on the concept of the resilience, assuming that definitions of other relevant concepts, such as power system reliability, security and stability are known and can be found in e.g. [16], [17]. We briefly discuss here the relationship between the mentioned concepts, what is expected to more precisely define the paper scope. Reliability focuses on the system ability of uninterruptibly supplying customers, also during highly probable contingencies treated as $N$-1 or $N$-2 events. On contrary, disruptive, extreme events are relevant for resilience assessment [18]. Security, the ability to withstand sudden disturbances, together with adequacy, can be seen as a part of the reliability requirements. The following two major aspects, relating resilience and security to each other, can be identified:

- States: preventive, emergency and restorative states are used in power system security to describe the operating states in normal operation, violated operation and when parts of the system lost power, respectively [19]. In addition, normal, alert, emergency, extreme and restorative states are used to describe power system conditions [20]. Different resilience levels also correspond to these power system states [21]. Understanding the concept of resilience has to do with transitions of the power system through different states, in which some of security constraints are satisfied, or not.
- Contingencies: as known, power system security is the ability of a power system to withstand contingencies/perturbations and remain in its secure state, or to operate within its acceptable limits. If the limits, expressed as equality and inequality constraints are breached, the system state will move from the normal state to another state, e.g. alert, emergency or extreme state [20]. On the other hand, power system resilience is an expression of the degree of the system capability to withstand a massive contingency, e.g. the one caused by an extreme low probability and highly impact event, in which it is not about outage of 1, 2, or several system elements, but outage, simultaneous, or sequential, of a larger number of system components.

Stability is also a time-varying attribute. A system can be stable in a new operating equilibrium after a disturbance, but at the same time insecure [16]. A power system with vulnerabilities in the fuel supply can have fuel security problem [22]. Such a problem can be perceived as a MES security problem, for example, the disruption of gas supply for a gas turbine caused by vulnerable gas generation and pipelines. Regarding flexibility, these are different definitions for a MES [23] and for power systems [24]. Both definitions focus on the ability to optimally manage the variability and uncertainty originating from the renewable power generation and loads. In [25], flexibility, together with resilience and connectivity, are perceived as the fundamental attributes of future sustainable power systems.

## III. Modelling and Quantification of MES resilience

To assess the degree or the status of MES resilience, modelling and quantification methods of the MES resilience are essential to be understood. There has been a comprehensive literature review on power system resilience quantification metrics [26]. However, a review of the MES resilience quantification methods has not yet been fully addressed. Based on the open literature sources, MES system resilience quantification methods can be classified into three groups. Each group has a different resilience quantification perspective, as follows: 1) temporal aspect and resilience level/degree time variations, 2) risk analysis of consequences of disruptive events, and 3) spatial information of the MES networks and disruptive events. Advantages and disadvantages of each group are also discussed.

### A. Multi-temporal resilience metrics

The resilience quantification framework of a typical critical infrastructure, the *resilience triangle*, was proposed in [27] to represent the loss of functionality from disruptive events, and the resilience varying over time. However, this metric cannot quantify for how long the system states lasted before the restoration phase has started and how quickly the resilience level degraded. To address these challenges, the *resilience trapezoid*, in [28] was proposed and applied for power system resilience assessment. This framework is characterized by describing the time-dependent resilience level in the following three phases: 1) disturbance progress, 2) post-disturbance and 3) restorative state.

According to [12], resilience aims to take into account the impact of large disruptions to the system infrastructure, customers and control room staff. Therefore, the existing literature on power system and MES resilience, $r$, modelling methods is grouped by the performance of networks [29], system operation [30], and loads [31]–[33].

In [29], resilience $r$ is modelled as the MES network efficiency by summing up the distances $d_{ij}$ of the shortest path between nodes $i, j$ in the network, i.e.

$$r = \frac{1}{N(N-1)} \sum_{i \neq j} \frac{1}{d_{ij}} \, , \tag{1}$$

where $N$ is the total number of nodes in a network including different energy vectors. The quantification method can indicate the effectiveness of energy flow influenced by the failure propagation between energy vectors through coupling system components. In [30] the system resilience $r$ is modelled as the exponential of negative ratio of the increase in MES operation costs $\gamma$ due to disruptive events, i.e.

$$r = \exp\left(-\frac{(\gamma - \gamma_0)}{M}\right) \, , \tag{2}$$

where $\gamma_0$ is the operation cost during the normal operation, and $M$ is the total energy resource. However, both models ignore the time window covering all three phases of resilience. To address the temporal variation of the resilience, it is important to consider the time of the system spent in each phase. In [31], the temporal variation of the resilience $r$ is addressed by different diurnal and seasonal periods of the year. Resilience is quantified by the system cost caused by the loss of service, i.e. undelivered electricity, heat, or gas, as a result of the disruption. Such a quantification metric has the following three dimensions: time, failure mode and functional service. However, the quantification methods mentioned above use deterministic-based modelling of disruptive events, not addressing the stochastic nature, e.g. probability, of the large scale contingencies. In [32], duration of phases II and III are modelled through the Monte Carlo Simulation (MCS) method, introducing the stochastic nature of the problem. In addition, for the purpose of MES modelling, the information about the disconnected load (load shedding) in all individual energy vectors, was used.

### B. Risk-based metrics

On the other hand, the risk-based resilience quantification methods are investigated to address the low probability characteristics of the disruptive events. Here, the resilience is represented by the probability-based risk. The catastrophe model was used as the basis of the risk assessment of the natural hazard, including the components of hazard, inventory (e.g. locations of power lines), vulnerability, and loss [34].

Risk-based quantification methods have been traditionally applied in power system studies. In [35] the information about the vulnerability of electrical overhead transmission lines, modelled by fragility curves, was used to quantify the power system resilience. In this approach, locations of faults, probability of the severity of faults and event occurrences, are considered. In [36] and [37] a risk assessment framework for classifying the risk of failures in distribution and transmission networks are respectively proposed. In particular, the risk considered in [36] varies over time, outage locations and type of the disruptive event. It is expressed as a conditional probability $p(f|\mathbf{X}) \cdot \mathrm{C}^{\mathrm{TOTAL}}$, where $p(f|\mathbf{X})$ is the probability of line outages depending on external conditions such as extreme wind speed, or lightning, and $\mathrm{C}^{\mathrm{TOTAL}}$ is the energy supply interruption costs. Further risk mitigation through control actions of demand response to increase the power system resilience is discussed in [38]. However, in these studies the risk assessment methods applied to MES resilience problem are ignored.

In [39], a conceptual framework for developing resilience metrics of MES is given. More specifically, a tail-oriented statistic such as Conditional Value-at-Risk (CVaR) was deployed to minimize the risk of economic losses under low probability and high impact disruptive events. To quantify MES resilience, the resilience of individual energy vectors needs to be normalized. Such a normalization method can make the resilience of different energy vectors characterized by different rated power and operating states comparable. Moreover, a trade-off between different objective functions in risk assessment, e.g. minimum economic losses versus recovery costs, is needed to take into account different disruptive consequences. The correlation of the tail-oriented statistics should also be considered. Dimension reduction of the simulation-based generation of the disruption impacts and restoration methods, such as the sequence of failures and restoration actions, needs to be further taken into account.

### *C. Spatial resilience metrics*

In the two quantification metrics mentioned above, the temporal variations and the resilience level uncertainty are mainly addressed. However, the network topology and contingency locations were ignored in the quantification process, which is particularly important for large-scale and interdependent networks, such as those belonging to a single MES.

Graph-theoretical approaches have been used to describe the topological properties of networks by vertices/nodes and edges/links. The Laplacian matrix of a graph was used in [40] to describe the electrical and graphical features of a power system. A mathematical theory based on the matrix was proposed to localize failures in a cascading process of line outages. Therefore, both topological features and power flow can be further used to model failures in the process of the MES resilience quantification. In [41], [42], the presented simulation results indicate that interdependent networks are more vulnerable to cascading failures than the individual network. In addition, an interdependent network with more inter-edges (connected nodes belonging to different networks of a single MES) per node has higher resilience against cascading failures.

Other than topology, the spatial characteristics of extreme weather and coupling units are considered in the resilience quantification of an integrated power and gas system [43]. Considering the existence of the coupling technologies like gas turbines and compressors, the contingency propagation between the electricity and gas vectors has to be modelled. The results indicate the system coupling amplifies the load curtailment caused by hurricanes. Furthermore, [44] considers spatial characteristics of the distribution system (locations of sources and loads) and the transportation system (electric buses traveling distance as generation resources) in resilience quantification.

A detailed review of the power system and MES resilience quantification methods is shown in Table I.

## IV. MLBTs Applied to MES Resilience Assessment

In recent decades, applications of MLBTs suitable for assessing MES resilience and related problems have been studied. As discussed in Section II, the concepts of power system security and reliability are relevant for understanding and quantifying resilience. In particular, the operating system states after disruptive events are the same for the security and resilience assessment. Therefore, MLBTs applied to power system security assessment under *N-1* or *N-2* contingencies can be extended to resilience assessment under extreme events. Recent progress in application of MLBTs for power system reliability management has been comprehensively reviewed in [4]. Lots of attention has been put on static and dynamic security assessment and approaches for determining stability limits.

There are several terms from MLBTs [45] are used in the following discussion. The term *training data set* is used in the MLBTs to build a prediction model (a *learner*) to predict the *outcome*, such as MES resilience, given the input measurements (*features*). When the outcome is a class variable (e.g. system secure/insecure, resilience level high/medium/low), the learning problem is a *classification* problem. The outcome classes can be seen as *labels*. When the outcome is quantitative, the learning problem is a *regression* problem. Both problems are called *supervised learning* problems. When the data set has no outcome measurement, the learning problem is a *clustering* problem to describe how the data are organized or clustered. This is called a *unsupervised learning* problem. In reinforcement learning, the *learner* is an agent that take *actions* to change *states* for maximum *rewards* in an environment. Reinforcement learning is neither a *supervised learning* nor an *unsupervised learning* problem.

In this section, MLBT applications related to MES resilience assessment are discussed and more specifically related to the following power system and MES applications: 1) network characteristics determination 2) prediction of the system operation performance and 3) load curtailment prediction.

### *A. Network characteristics determination*

MLBTs can be used to automatically, fast, robustly and accurately identify the geographical and topological information of a large and complex power/heating/gas network. It can help to quickly assess the resilience of the system based on the topological MES features, especially an interdependent network such as a MES. The resilience could be in particular quantified by the spatial resilience metrics discussed in Section III, where the network topology was used as an input for the assessment.

In [46], a strong linear interdependence between power system resilience and network topological features, e.g. degree, path length and order of the networks, was validated by the Pearson correlation. Other than the topological features, line parameters can also influence the system resilience. The two features were embedded through the graph convolution neural network (GCNN) to reduce the feature dimension for the K-means based clustering of the gas network resilience in [47]. A case study on a large-scale gas pipeline network then verified that pipelines with similar embedded features have similar risk levels. However, the data set for clustering has no outcome measurements for resilience (labels). The resilience of all networks needs to be pre- or post-calculated by the quantification metrics. Reference [48] deployed a convolutional neural network (CNN) method for classifying a power and natural gas interdependent network topology into a “scale-free network” (a network can be described by power law distributions), a “small-world network” (high clustering nodes with a small diameter) and a “random network” [49] through the adjacency matrices. The resilience assessment of different types of network topology and coupling characteristics (coupling degree and order based on [50]) was then performed based on the energy supply for loads. However, the network topology and resilience variations in the propagation of contingencies were ignored.

TABLE I
COMPARISON OF SELECTED QUANTIFICATION METHODS FOR POWER SYSTEM AND MES RESILIENCE
SYSTEM TYPE: ELECTRICITY VECTOR (E), HEATING VECTOR (H) AND GAS VECTOR (G)

| Ref. | System type | Event type | Resilience phase | Quantification metrics | Temporal/Spatial variations of resilience level | Resilience level model |
|---|---|---|---|---|---|---|
| [28] | E, transmission network | Windstorm, transmission line and tower failure | I - III | Resilience trapezoid | Temporal | Percentage of operational grid, generation and load |
| [29] | E, G, distribution network | Gas supply outage | I - III | Resilience trapezoid | Temporal/MES topology, contingency propagation between networks | Network efficiency |
| [30] | E, H, G, MES microgrid | Cyber threat, distribution line outage | II III | Resilience trapezoid and encryption cost | Temporal | Operation cost |
| [31] | E, H, G, distribution network | Boiler, compressor, gas and power grid failure | I - III | Resilience trapezoid, (three-dimension of time, failure mode and system functional service) | Temporal | Operation cost and penalty cost due to energy service loss |
| [32] | E, H, G, distribution network | Windstorm, overhead line, underground cable and electrical substation failure | I - III | Resilience trapezoid, total load curtailment, collapse ratio and recovery ratio of resilience level | Temporal | Total load curtailment percentage weighted by initial load of each energy vector |
| [35] | E, transmission network | Windstorm, overhead line outage | II | Risk assessment | – /Fault location | Vulnerability by fragility curve, probability of fault severity and windstorm occurrence |
| [36] | E, distribution network | Thunderstorm, lightning, windstorm, line outage | II | Risk assessment | Temporal/Network geographical information | Classification of risk, probability of failure and impact cost |
| [38] | E, distribution network | Lightening, distribution line outage | II III | Risk assessment | Temporal/Network geographical information | Classification of risk, probability of failure and impact cost |
| [39] | G, transmission network | Earthquake, gas pipeline and gas storage outage | II | Risk assessment | – /Fault location | CVaR |
| [43] | E, G, transmission network | Hurricane, transmission tower and conductor failure | II III | Resilience trapezoid, total cost of gas and power load shedding, asset damage | Temporal/Failure probability varying in hurricane location | Power and gas demand not supplied |
| [44] | E, transport vector, distribution network | Hurricane, power source and line failure | III | Resilience trapezoid and allocation cost | Temporal/Power system restoration path | Total power supply weighted by load priority |

Reference [51] further determined the sequence of the worst impact zones in the IEEE 123-node distribution network by the Q-learning algorithm. In the paper, the propagation of line outage and generation loss caused by a hurricane was modelled, where the topological information of the network represents *states*, the propagation of events to another zone stands for *actions* and the impact is seen as *rewards*. Such a study can help to assess the system resilience and schedule restoration actions based on the sequence of failures. The method could be further applied to a MES and a larger scale transmission system, and temporal features during the propagation should be considered.

### *B. Prediction of the system operation performance*

In this subsection, MLBTs applied to the system resilience assessment, based on the operation performance, are discussed. In particular, MLBTs applied to power system security and reliability assessment are scrutinized. The system performance like operating state, power flow, power outputs of the committed generators and voltage magnitudes are predicted as a part of the static security assessment.

Traditionally, the security constrained optimal power flow (SCOPF) model is applied to meet the *N-1* contingency criterion with the minimum cost. However, the high computational requirements of the SCOPF simulation under each contingency based on the MCS make the security assessment not tractable. In [52], extreme randomized trees and Feedforward Neural Network (FFNN) method were used to build a *proxy* $y_p$, which is a component that can predict the real-time operation cost $y$, based on the system performance $\xi_{\mathrm{nd}}$. Such a *proxy* can greatly reduce the simulation time. Results of a *N-1* contingency of a transmission system verified that the computational time is reduced by a factor of 9-16 times without jeopardizing the prediction accuracy, compared to the MCS-based method. In [53], the security assessment is also predicted by the FFNN, while the security level is quantified through a hyper-ellipse box by the normalized margin between the security limit and the system performance, power flow and voltage magnitudes. The security levels are then classified and ranked based on the margin through a created rule-based method. On the other hand, as presented in [54], using two FFNNs the security margin under large variations of the wind power is predicted by the joint cumulative distribution functions of the multiple security margins. Such a model requires no assumptions on the distribution of the margins. The test results verified that the model outperforms the multivariate kernel density estimation and the copula based models.

The performance of the abovementioned FFNN-based methods is evaluated based on the training and test data set. It was found that that they are sensitive to adversarial perturbations, in the context that they can lead to incorrect classification [55]. Reference [56] proposed a framework to obtain the guarantees of neural network behaviors, wherein the input regions without adversarial examples are determined. Such a framework enables a better understanding of the neural network and how to apply it in real-time operation in practice.

On the other hand, the security rules of security state classification have been integrated in the machine learning training process but not been fully interpreted. In [57], the *decision tree depth* approach was used as the intepretability of decision tree methods applied for the classification. A tradeoff between the predictive accuracy and the intepretability is also presented through the optimal tree and greedy optimization-based tree learning approaches. Such a work can further increase the trust about the security rules learned from the MLBTs.

Besides the system security states, the operation cost is also quantified for resilience assessment as mentioned in (2) in Section III. In [58], the restoration actions of dispatching the restoring power are determined by a proposed deep reinforcement learning (DRL) method. To overcome the scalability issue of the standard DRL, where the action space is proportional to the number of units and power output levels, the proposed method decomposes the collective actions into sequential Markov decision process to make fast real-time decisions. Similarly, [59] predicts the operation costs including generation redispatch cost, load shedding cost and wind power curtailment cost under the *N-1* contingency through a proposed *proxy*. The *proxy* is a real-time decision making simulator with built-in MLBTs, which utilizes the K-means clustering and MCS methods to assess the next-day operation cost.

In the context of the MES resilience assessment, as far as we know, there have not been studies investigating the application of the MLBTs for direct prediction of the system performance under contingencies from the system operation perspective. In [60], a FFNN is applied to predict power/gas output for the fast economic dispatch in an integrated electricity and gas system under normal operation. Compared to the second-order cone programming (SOCP) model of the non-convex energy flow, here the proposed method has higher prediction accuracy. The computational time is also $10^4 - 10^5$ times faster than the model-driven piecewise linearization method and the SOCP. It is noted that the MES operation states, such as nodal pressures and gas flows, are then recovered after the FFNN. These states are not the outcome of the FFNN and need to be resolved through the physical model with the outcome.

### C. Load curtailment prediction

In this subsection, the system security assessment is focused on the performance of the demand side, particularly the load curtailment provoked by contingencies. Here, the load shedding can be used as the emergency control action following extreme contingencies that lead to massive power imbalances and a system frequency decline. In the text below, the MLBTs applied for the load curtailment prediction are discussed.

In [61], a decision tree classifier was deployed to predict the system security status, safe/unsafe. The status represents whether or not load curtailment exists after contingencies. A novel deep autoencoder feature extraction framework was applied to extract efficient representative features for the decision tree classifier. The training features are firstly extracted through a novel deep autoencoder feature extraction framework for the classification. Reference [62] demonstrated a classifier of different preventive actions (e.g. number of islands to be created by the operators to stop cascading events and to prevent the collapse of the entire power system) with the Support Vector Machine (SVM) method. Based on the features of the event parameters, the SVM method was applied to predict effective preventive actions leading to a minimum number of customers not supplied by the electricity. Case studies indicated that the performance of the proposed SVM has a close accuracy with the ideal classifier, but with significantly shorter computational time.

In addition, due to the low probability of extreme events, there is a challenge of imbalanced classes, safe/unsafe labels, in the data set. The safe class (majority class) has a much higher number of observations than the unsafe class (minority class) has. This challenge could further lead to inaccurate classification such as classifying unsafe status as the safe one. In [61], a data pre-processing method based on bi-variate R-vine copulas sampling was proposed to enrich the historical data of uncertainties from loads and wind power generation. With the enriched observations of uncertainties, the training set with the label of insecure operating state is enriched leading to more effective classification procedure later.

In Table II, a review of MLBTs applied to power system and MES resilience assessment related problems is presented.

## V. Future Research Agenda

In this section, the most relevant research questions related to a) modelling and quantification of MES resilience and b) application of MLBTs for MES resilience assessment, are identified. Furthermore, insights and guidelines for future research directions on these two groups of identified research questions are provided.

### A. Future directions in MES resilience quantification

From the review of the MES resilience quantification methods in Section III, the following unresolved research questions can be identified:

1) How can resilience from different energy vectors be combined to assess the overall system resilience?
2) How can the MES resilience be quantified when component failures occurring in different energy vectors are correlated to each other?
3) How can the MES risk analysis be undertaken based on tail-oriented statistics and correlation between the probability distribution of consequences to each energy vector?
4) How is the MES resilience level changed with the contingency propagation through different energy vectors? What is the impact of the contingency location?
5) What would be the impact of novel smart grid technologies and solutions to MES resilience? How SIPSs supported by Phasor Measurement Units (PMUs) and fast and cyber

TABLE II
REVIEW OF THE MLBTS FOR POWER SYSTEM AND MES RESILIENCE ASSESSMENT

| Application groups | MLBT | MLBT applications | Ref. |
|---|---|---|---|
| Network characteristics determinination | K-means clustering | Natural gas pipeline grouping | [47] |
| | CNN | Reduce feature dimensions and measure similarities among nodes | [47] |
| | | Classification of integrated power and gas networks | [48] |
| | Reinforcement learning | Determine the sequence of outage propagation | [51] |
| | Linear regression | Relations between electrical network features and system resilience | [46] |
| Prediction of system operation performance | FFNN | Operation costs | [52] |
| | | Line flow and bus voltage | [53] |
| | | Power system security margin | [54] |
| | | Classification of safe/unsafe operation (violation of generator and line limits) | [56] |
| | | Energy flow of power and gas | [60] |
| | Decision trees | Classification of safe/unsafe operation (violation of phase angles and internal voltage of generators limits) | [57] |
| Load curtailment prediction | Autoencoders | Feature extraction for better classification by a classifier | [61] |
| | Decision trees | Classification of safe/unsafe operation (load curtailment) | [61] |
| | SVM | Decision making of preventive actions for minimum expected load not supplied | [62] |

secure communication [63] infrastructure could contribute to the system resilience?
6) What would be the cost of the design of advanced SIPS for busting system resilience?

The resilience of each energy vector is traditionally monitored and quantified within the vector in question. Resulting from the mutual coupling, the resilience levels of individual vectors are correlated to each other in terms of time, contingency location and intensity. The awareness of other vectors' network topology, operating states and risks under contingencies can contribute to the whole MES resilience quantification. The quantified MES resilience can further help to schedule preventive and restoration actions for resilience enhancement. Such quantification should in particular address the characteristics of the low probability and high impact events, and correlation between these events and their impacts.

Therefore, the following research directions for exploring the above research questions can be identified:

1) Development of new normalization methods of resilience of individual energy vectors for quantification of the overall MES resilience.
2) Modelling of joint probability distribution of two simultaneous outages occurring in different energy vectors as a result of a single disruptive event.
3) Risk analysis of a MES based on tail-oriented statistics and correlation between the probability distribution of consequences to each energy vector.
4) Consideration of different speeds of the propagation of cascading failures in different energy vectors.
5) Assessment of communication networks and data analytics for resilient MES [64]. The variety of a broad spectrum of sensors for data acquisition, as well as communication network speeds, but also the requirement for time synchronization of different sensors might be potential challenging practical implementation questions.
6) Related to extensive implementation of communication infrastructure, consider its impact to the resilience, but from the perspective that it can also be negatively affected by the extreme events.

To partly demonstrate the research questions and research directions identified above, in Figs. 1 and 2 an illustration of the MES resilience is shown. In Fig. 1, the electricity, gas/hydrogen and heating vectors are integrated into a single MES through the coupling technologies/units, such as gas compressors, electric heating units and combined heat and power plants. Meanwhile in Fig. 2, the resilience trapezoid in [28] is extended with the resilience level varying in the location in the network (e.g. nodes) as well as energy vectors. The resilience level of each energy vector is influenced by the cascading failures triggered by disruptive events, which is a recursive process of failures within a single network and between different networks. Due to different topologies and nature of individual energy vectors and different time constants, describing the speed of transient processes, the MES resilience varies in time and depends on the perturbation location.

### B. Future directions of MLBTs applied to MES resilience assessment

From the state-of-the-art analysis about MLBTs for MES resilience assessment mentioned in Section IV, it can be

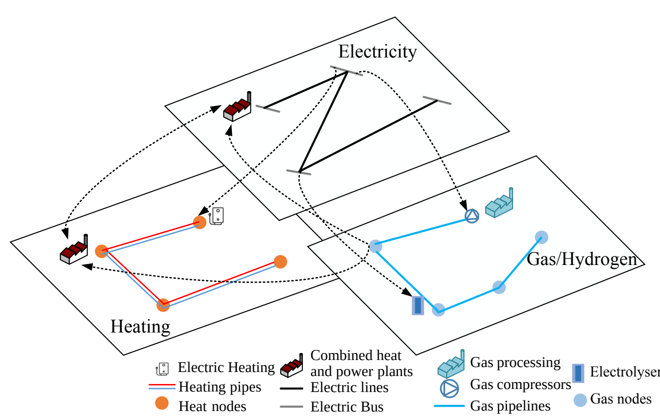


Fig. 1. A MES of electricity, heating and gas/hydrogen vectors integrated with coupling technologies

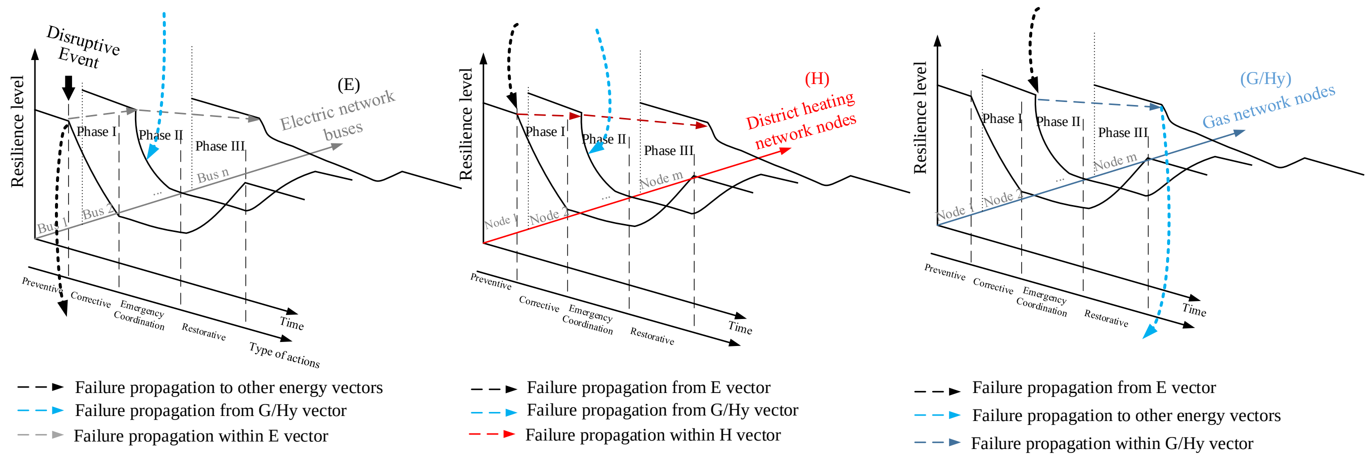


Fig. 2. Resilience trapezoids of individual energy vectors (electricity (E), heating (H) and gas/hydrogen (G/Hy)) under disruptive events

concluded that there has not been sufficient focus on 1) MES network characteristics determination, 2) MES system operation performance prediction and 3) MES load curtailment prediction. Therefore, the following research questions can be identified:

1) What is the relationship between MES topology characteristics and the system resilience?
2) In the context of the increased level of uncertainties, can large quantities of data about operating states from all energy systems contribute to the trust and efficiency of the MES resilience assessment?
3) In the context of enhancing MES resilience, how to increase the trust and efficacy of the MLBT obtained sequences and plans for load shedding in different energy systems?
4) How can the control room staff more efficiently learn from the historical data about the low probability and high impact events?

The usage of MLBTs could contribute to automatically, accurately and efficiently assess the MES resilience. In particular, the large-scale network characteristics, the non-convex optimization considering network constraints, and manual simulations by operators, could lead to the resilience assessment slowly and with bias. Supervised learning methods such as FFNN and K-nearest neighbor methods can be used for resilience level prediction, classification and ranking. The training data set has the features of network topology, network parameters, operation costs, operating states, and labels of resilience levels or resilience classes quantified by the quantification methods. On the other hand, unsupervised learning such as the K-means clustering method can be used to assess and group the MES resilience by their network similarities. It could be applied to data sets that have no labels related to resilience but only features of network topology and parameters, on condition that the resilience levels are proved to be related to the network types. Furthermore, DRL can be used for fast and accurate decision making to enhance the resilience. For example, DRL is used to determine the restoration and preventive action sequences, and to identify the cascading failure sequence with the worst impact. Challenges of these MLBT applications could be the high dimensional features from all energy vectors. Therefore, feature extraction or selection techniques need to be adopted for further resilience prediction and classification. In addition, lack of operation data under the disruptive events can lead to imbalance data/classes and inaccurate classification prediction. Therefore, a new sampling method of the data set is needed to enrich the minority class and to improve the prediction accuracy. Large-scale MES with many possible actions such as load shedding of different energy vectors could make the DRL not efficient.

Therefore, the following research directions that could further address the research questions from Section V. B can be identified:

1) Application of MLBTs, e.g. DRL, for determining failure propagation sequences in MES. Here topological MES features can be used to ensure reliable results.
2) MES resilience, or resilience class prediction using supervised learning. Here the resilience quantification can be based on the assessment of the system performance judged by a selected set of the system attributes.
3) Design of DRL-based approaches for the prediction of the MES load shedding plans/sequences. It is expected that this will significantly enhance the overall MES resilience.
4) Development of feature selection/extraction methods for reducing the space/dimension of MES features, for improving computational efficacy of resilience assessment. It is expected that features like operation performance and network topology could be of particular use.
5) Development of methods for enriching available data sets in the process of e.g. deep learning-based MES resilience assessment. It is known that for example the R-vine copula-based model can be used to sample historical data and generate large populations of anticipated system states needed for training purposes. Such methods can help generating a higher quality data sets that can make MLBTs to be more robust and accurate.
6) Design of advanced SIPS based on MLBTs for enhancing MES resilience.

## VI. Conclusions

In this paper, power system and MES resilience definitions, as well as the relevant concepts are presented in Section II. Here, the differences between power system resilience and security, which are two concepts closely related to each other, are identified. In Section III, the recent state-of-the-art on MES and power system resilience modelling approaches and quantification methods, e.g. 1) multi-temporal resilience metrics, 2) risk-based metrics, and 3) spatial resilience metrics, is reviewed. Each of these methods has their own characteristics and angle for resilience quantification. Group 1) focuses on temporal variations of the resilience, split into the following three phases: a) resilience disturbance progress, b) post-disturbance degraded and c) restorative states. The resilience indicators are represented by network efficiency, operation costs and load curtailment. Group 2) quantifies the resilience by the risk level of the system and considers the probability distribution of consequences of the disruptive events. The tail-oriented statistics is deployed to address the consequences of low probability and high impact events on the probability distribution. Group 3) focuses on spatial information of the system and disruptive events, which are directly related to the resilience level. Such information includes topological and network properties of the network, and the location of the events and contingencies.

In Section IV, MLBTs applied to MES resilience assessment were discussed. The basic machine learning terms commonly used in the resilience assessment literature are firstly introduced. Then the existing literature is grouped by applications into 1) network characteristics determination, 2) prediction of the system operation performance, and 3) load curtailment prediction. Each group utilizes different MLBTs and different data features to predict resilience levels/classes, to determine the failure sequences, or to determine the optimal restoration sequence. In particular, in Group 1), the graph theory was applied to determine the network characteristics necessary for resilience prediction. In addition, in Group 2), the power system security assessment was comprehensively reviewed and the potential of those MLBTs extended to resilience assessment was further discussed. In Group 3), in addition to the prediction of resilience, the preventive actions and data set enrichment using MLBTs were introduced.

In Section V, based on the above discussed literature on MES resilience quantification and MLBTs applied to MES resilience assessment, unresolved research questions and future research directions are identified. These questions are raised from each group of approaches for resilience quantification. For example, Group 1): the normalization methods of the resilience levels/indicators of individual energy vectors are needed, Group 2): the probability distributions of the consequences on each energy vector from the same event are always correlated, and Group 3) the spatial information of different energy vectors needs to be addressed to model the contingency propagation. An illustration of the MES resilience trapezoid was then proposed to better demonstrate the identified future research directions.

Furthermore, from each group of the MLBTs applied to MES resilience assessment, the unsolved research questions and future research directions were identified. For example, Group 1) utilization of topological features of a MES using MLBTs to determine the failure propagation sequence. Group 2) development of supervised learning methods to predict/classify the MES resilience levels/classes. Group 3) determination of the load shedding plans using DRL, and enrichment of the minority class of not resilience levels in training data set for a better classification.

This paper brings the awareness of this timely and important research area. It also identifies the unsolved and relevant problems and proposes an outlook for future research directions. These future directions can also be seen as a control room decision supporting tool for effective, precise and fast MES resilience assessment based on MLBTs. In advanced cases decisions can be undertaken autonomously, without control room man power engagement. Here the concepts based on SIPSs are good candidates for this kind of fast and effective actions. These must be however based on advanced smart grid technologies, e.g. synchronized measurement technology supported by cyber secure communication infrastructure.

## References


[1] S. Wilde, "9 august 2019 power outage report," London, UK, Tech. Rep., January 2020.

[2] A. E. M. Operator, "Black system south australia 28 september 2016," Tech. Rep., March 2017.

[3] J.W. Busby, et al., "Cascading risks: Understanding the 2021 winter blackout in texas," *Energy Research and Social Science*, vol. 77, p. 102106, 2021.

[4] L. Duchesne, E. Karangelos, and L. Wehenkel, "Recent developments in machine learning for energy systems reliability management," *Proceedings of the IEEE*, vol. 108, no. 9, pp. 1656–1676, 2020.

[5] J. Xie, I. Alvarez-Fernandez, and W. Sun, "A review of machine learning applications in power system resilience," *IEEE Power and Energy Society General Meeting*, vol. 2020-, p. 9282137, 2020.

[6] S. Yang, B. Vaagensmith, and D. Patra, "Power grid contingency analysis with machine learning: A brief survey and prospects," *2020 Resilience Week, Rws 2020*, pp. 119–125, 2020.

[7] M. J. Kim, T. S. Kim, R. J. Flores, and J. Brouwer, "Neural-network-based optimization for economic dispatch of combined heat and power systems," *Applied Energy*, vol. 265, p. 114785, 2020.

[8] Q. Hong, et al., "Design and validation of a wide area monitoring and control system for fast frequency response," *IEEE Transactions on Smart Grid*, vol. 11, no. 4, pp. 3394–3404, 2020.

[9] L. Ding, Z. Ma, P. Wall, and V. Terzija, "Graph spectra based controlled islanding for low inertia power systems," *IEEE Transactions on Power Delivery*, vol. 32, no. 1, pp. 302–309, 2017.

[10] L. Ding, Y. Guo, P. Wall, K. Sun, and V. Terzija, "Identifying the timing of controlled islanding using a controlling uep based method," *IEEE Transactions on Power Systems*, vol. 33, no. 6, pp. 5913–5922, 2018.

[11] E. S. Paidi, H. Marzooghi, J. Yu, and V. Terzija, "Development and validation of artificial neural network-based tools for forecasting of power system inertia with wind farms penetration," *IEEE Systems Journal*, vol. 14, no. 4, pp. 4978–4989, 2020.

[12] IEEE PES Industry Technical Support Task Force, "The definition and quantification of resilience," Tech. Rep., April 2018.

[13] M. Panteli and P. Mancarella, "The grid: Stronger, bigger, smarter?: Presenting a conceptual framework of power system resilience," *IEEE Power and Energy Magazine*, vol. 13, no. 3, pp. 58–66, 2015.

[14] Z. Bie, Y. Lin, G. Li, and F. Li, "Battling the extreme: A study on the power system resilience," *Proceedings of the IEEE*, vol. 105, no. 7, pp. 1253–1266, 2017.

[15] CIGRE C4.47 Power System Resilience Working Group, "Resilience of interdependent critical infrastructure," Tech. Rep., February 2022.

[16] P. Kundur, et al., "Definition and classification of power system stability," *IEEE Transactions on Power Systems*, vol. 19, no. 3, pp. 1387–1401, 2004.

[17] N. Hatziargyriou, et al., "Definition and classification of power system stability – revisited amp; extended," *IEEE Transactions on Power Systems*, vol. 36, no. 4, pp. 3271–3281, 2021.

[18] R. Moreno,et al., "From reliability to resilience: Planning the grid against the extremes," *IEEE Power and Energy Magazine*, vol. 18, no. 4, pp. 41–53, 2020.

[19] T. E. Dy Liacco, "The adaptive reliability control system," *IEEE Transactions on Power Apparatus and Systems*, vol. PAS-86, no. 5, pp. 517–531, 1967.

[20] L. H. Fink and K. Carlsen, "Operating under stress and strain," vol. 15:3, 3 1978.

[21] M. Panteli and P. Mancarella, "Modeling and evaluating the resilience of critical electrical power infrastructure to extreme weather events," *Ieee Systems Journal*, vol. 11, no. 3, pp. 1733–1742, 2017.

[22] H. Chen, F. S. Bresler, M. E. Bryson, K. Seiler, and J. Monken, "Toward bulk power system resilience: Approaches for regional transmission operators," *IEEE Power and Energy Magazine*, vol. 18, no. 4, pp. 20–30, 2020.

[23] J. Wang, "Integrated energy systems – unleashing the flexibility between heat and power," Ph.D. dissertation, 2020.

[24] I. E. Agency, "Status of power system transformation 2019 – power system flexibility," Tech. Rep., May 2019.

[25] E. P. R. Institute, "Electric power system resiliency – challenges and opportunities," Electric Power Research Institute, California, USA, Tech. Rep. 3002007376, February 2016.

[26] S. Afzal, H. Mokhlis, H. Azil Lllias, N. Nadzirah Mansor, and H. Shareef, "State-of-the-art review on power system resilience and assessment techniques," *IET Generation, Transmission and Distribution*, vol. 14, no. 25, pp. 6107–6121, 2020.

[27] T. Natural Hazards, K. Tierney, and M. Bruneau, "Conceptualizing and measuring resilience a key to disaster loss reduction," 2009.

[28] M. Panteli, P. Mancarella, D. N. Trakas, E. Kyriakides, and N. D. Hatziargyriou, "Metrics and quantification of operational and infrastructure resilience in power systems," *IEEE Transactions on Power Systems*, vol. 32, no. 6, pp. 4732–4742, 2017.

[29] N. Yodo and T. Arfin, "A resilience assessment of an interdependent multi-energy system with microgrids," *Sustainable and Resilient Infrastructure*, vol. 6, no. 1-2, pp. 42–55, 2021.

[30] S. D. Manshadi and M. E. Khodayar, "Resilient operation of multiple energy carrier microgrids," *IEEE Transactions on Smart Grid*, vol. 6, no. 5, pp. 2283–2292, 2015.

[31] S. Moslehi and T. A. Reddy, "Sustainability of integrated energy systems: A performance-based resilience assessment methodology," *Applied Energy*, vol. 228, pp. 487–498, 2018.

[32] M. Bao, Y. Ding, M. Sang, D. Li, C. Shao, and J. Yan, "Modeling and evaluating nodal resilience of multi-energy systems under windstorms," *Applied Energy*, vol. 270, p. 115136, 2020.

[33] H. Zhang, T. Zhao, P. Wang, and S. Yao, "Power system resilience assessment considering of integrated natural gas system," *IET Conference Publications*, vol. 2017, no. 727, pp. 87–93, 2017.

[34] P. Grossi, *Catastrophe modeling : a new approach to managing risk*. Springer, 2005.

[35] S. Dunn, S. Wilkinson, D. Alderson, H. Fowler, and C. Galasso, "Fragility curves for assessing the resilience of electricity networks constructed from an extensive fault database," *Natural Hazards Review*, vol. 19, no. 1, p. 04017019, 2018.

[36] J. B. Leite, J. R. S. Mantovani, T. Dokic, Q. Yan, P. C. Chen, and M. Kezunovic, "Resiliency assessment in distribution networks using gis-based predictive risk analytics," *IEEE Transactions on Power Systems*, vol. 34, no. 6, pp. 4249–4257, 2019.

[37] P. Dehghanian, B. Zhang, T. Dokic, and M. Kezunovic, "Predictive risk analytics for weather-resilient operation of electric power systems," *IEEE Transactions on Sustainable Energy*, vol. 10, no. 1, pp. 3–15, 2019.

[38] J. B. Leite and M. Kezunovic, "Risk mitigation approaches for improved resilience in distribution networks," in *2020 IEEE PES Transmission Distribution Conference and Exhibition - Latin America (T D LA)*, 2020, pp. 1–6.

[39] J.P. Watson, et al., "Conceptual framework for developing resilience metrics for the electricity, oil, and gas sectors in the united states," 9 2014. [Online]. Available: https://www.osti.gov/biblio/1177743

[40] L. Guo, C. Liang, A. Zocca, S. H. Low, and A. Wierman, "Line failure localization of power networks part i: Non-cut outages," *IEEE Transactions on Power Systems*, vol. 36, no. 5, pp. 4140–4151, 2021.

[41] S. V. Buldyrev, R. Parshani, G. Paul, H. E. Stanley, and S. Havlin, "Catastrophic cascade of failures in interdependent networks," *Nature*, vol. 464, no. 7291, pp. 1025–1028, 2010.

[42] D. H. Shin, D. Qian, and J. Zhang, "Cascading effects in interdependent networks," *IEEE Network*, vol. 28, no. 4, p. 6863136, 2014.

[43] H. Zhang, P. Wang, S. Yao, X. Liu, and T. Zhao, "Resilience assessment of interdependent energy systems under hurricanes," *IEEE Transactions on Power Systems*, vol. 35, no. 5, pp. 3682–3694, 2020.

[44] H. Gao, Y. Chen, S. Mei, S. Huang, and Y. Xu, "Resilience-oriented pre-hurricane resource allocation in distribution systems considering electric buses," *Proceedings of the IEEE*, vol. 105, no. 7, pp. 1214–1233, 2017.

[45] T. Hastie, R. Tibshirani, and J. Friedman, *The Elements of Statistical Learning*, ser. Springer Series in Statistics. New York, NY, USA: Springer New York Inc., 2001.

[46] M. Bessani, et al., "Probabilistic assessment of power distribution systems resilience under extreme weather," *IEEE Systems Journal*, vol. 13, no. 2, pp. 1747–1756, 2019.

[47] Y. Yang, S. Li, and P. Zhang, "Data-driven accident consequence assessment on urban gas pipeline network based on machine learning," *Reliability Engineering and System Safety*, vol. 219, p. 108216, 2021.

[48] S. Wang, X. Gu, S. Luan, and M. Zhao, "Resilience analysis of interdependent critical infrastructure systems considering deep learning and network theory," *International Journal of Critical Infrastructure Protection*, vol. 35, p. 100459, 2021.

[49] M. Kang and Z. Petrasek, "Random graphs: Theory and applications from nature to society to the brain," 2015.

[50] S. M. Rinaldi, J. P. Peerenboom, and T. K. Kelly, "Identifying, understanding, and analyzing critical infrastructure interdependencies," *IEEE control systems magazine*, vol. 21, no. 6, pp. 11–25, 2001.

[51] S. Paul, F. Ding, U. Kumar, W. Liu, and Z. Ni, "Q-learning-based impact assessment of propagating extreme weather on distribution grids," *IEEE Power and Energy Society General Meeting*, vol. 2020-, p. 9281506, 2020.

[52] L. Duchesne, E. Karangelos, and L. Wehenkel, "Using machine learning to enable probabilistic reliability assessment in operation planning," *20th Power Systems Computation Conference, Pscc 2018*, p. 8442566, 2018.

[53] R. Sunitha, R. S. Kumar, and A. T. Mathew, "Online static security assessment module using artificial neural networks," *IEEE Transactions on Power Systems*, vol. 28, no. 4, pp. 4328–4335, 2013.

[54] Z. Meng, Y. Guo, W. Tang, H. Sun, and W. Huang, "A multivariate density forecast approach for online power system security assessment," 2021.

[55] I. J. Goodfellow, J. Shlens, and C. Szegedy, "Explaining and harnessing adversarial examples," 2015.

[56] A. Venzke and S. Chatzivasileiadis, "Verification of neural network behaviour: Formal guarantees for power system applications," *IEEE Transactions on Smart Grid*, vol. 12, no. 1, pp. 383–397, 2021.

[57] J. L. Cremer, I. Konstantelos, and G. Strbac, "From optimization-based machine learning to interpretable security rules for operation," *IEEE Transactions on Power Systems*, vol. 34, no. 5, pp. 3826–3836, 2019.

[58] M. M. Hosseini and M. Parvania, "Resilient operation of distribution grids using deep reinforcement learning," *IEEE Transactions on Industrial Informatics*, vol. 18, no. 3, pp. 2100–2109, 2021.

[59] L. Duchesne, E. Karangelos, A. Sutera, and L. Wehenkel, "Machine learning for ranking day-ahead decisions in the context of short-term operation planning," *Electric Power Systems Research*, vol. 189, p. 106548, 2020.

[60] H. Liu, X. Shen, Q. Guo, and H. Sun, "A data-driven approach towards fast economic dispatch in electricity–gas coupled systems based on artificial neural network," *Applied Energy*, vol. 286, p. 116480, 2021.

[61] M. Sun, I. Konstantelos, and G. Strbac, "A deep learning-based feature extraction framework for system security assessment," *IEEE Transactions on Smart Grid*, vol. 10, no. 5, pp. 5007–5020, 2018.

[62] M. Noebels, R. Preece, and M. Panteli, "A machine learning approach for real-time selection of preventive actions improving power network resilience," *IET Generation, Transmission and Distribution*, vol. 16, no. 1, pp. 181–192, 2022.

[63] V. Terzija, et al., "Wide-area monitoring, protection, and control of future electric power networks," *Proceedings of the IEEE*, vol. 99, no. 1, p. 2060450, 2011.

[64] P.C. Taylor, et al., "An interdisciplinary research perspective on the future of multi-vector energy networks," *International Journal of Electrical Power & Energy Systems*, vol. 135, p. 107492, 2022.