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

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***Abstract*—Permanently increasing penetration of converter-interfaced generation and renewable energy sources (RESs) makes modern electrical power systems more vulnerable to low probability and high impact events, such as extreme weather, which could lead to severe contingencies, even blackouts. These contingencies can be further propagated to neighboring energy systems over coupling components/technologies 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 to solve various power system problems, including system planning, or security and reliability assessment. This paper aims to review MES resilience quantification methods and the application of MLBTs to assess the resilience level of future sustainable energy systems. The open research questions are identified and discussed, whereas the future research directions are identified.**

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

I. Introduction

DUE to an 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 sectors (e.g., heating, gas, or transportation) over the system assets coupling energy sectors 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 low probability and high impact events, e.g., earthquakes, hurricanes, and extremely cold weather conditions. In this context, quantification of the multi-energy system (MES) resilience, where different energy sectors 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 sectors' resilience levels and their specific dynamics expressed through time constants describing the speed of the 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 a significant number of benefits, compared to traditional and classical approaches, for example: *(i)* quickly reaching decisions, especially for large-scale non-convex physical models requiring very demanding computational efforts for problem solving, *(ii)* achieving highly accurate decisions, compared to those traditional approaches, e.g., based on model order reduction, or linearization, *(iii)* utilizing massive historical data sets collected by a large number of sensors described by a high reporting rate, *(iv)* simulation of a broad range of scenarios taking into account different sources of uncertainties, *(v)* forecasting future system conditions, or states, *(vi)* improved forecasting accuracy by physics-informed machine learning methods which integrate the historical data and physical laws of systems, and *(vii)* automatically controlling the grid and ensuring system stable operation in cases of human errors, or delay in human reactions. Resulting from the increased complexity of some of protection functions, particularly those related to System Integrity Protection Schemes (SIPS), e.g. underfrequency/undervoltage load shedding [4], intentional controlled system islanding [5], [6], or monitoring of power system attributes required by novel and smart technology solutions, approaches based on ultimately data-driven solutions supported by MLBTs, become

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the solutions applicable today [7].

In the past, MLBTs have been applied to power systems for various purposes, including reliability management [8], system stability assessment and control [9], frequency analysis and control [10], and contingency analysis [11]. In addition, MLBTs were also used for solving economic dispatch of a MES during normal operation [12]. MLBTs have also been utilized for short-term system status prediction/assessment, system stability control and long-term system planning. As a type of supervised learning, tree-based methods such as decision trees were applied to transient stability [13] and voltage stability assessment [14]. Neural networks such as extreme learning machine (ELM) [15] and convolutional neural networks (CNNs) [16] were used for frequency stability assessment. In [14] and [7] artificial neural networks (ANNs) were used for voltage stability and system inertia prediction. Support vector machines (SVMs) were applied to frequency and voltage stability assessment in [17] [14], and transient stability control in [18]. The long short term memory (LSTM) approach was applied to distributed energy resource (DER) sizing in [19]. In [20] unsupervised learning, such as clustering method, was adopted for DER allocation. Reinforcement learning methods, such as deep reinforcement learning (DRL), were applied to frequency stability control [21] and DER sizing [22]. The Q-learning method was used in grid hardening problem in [23]. A review paper [9] focuses on the MLBTs applied to power system resilience enhancement considering four aspects, power outage forecasting, stability assessment, stability control and system restoration. However, these issues are directly related mainly to electrical power systems, but not explicitly on MESs. Furthermore, there is a gap of understanding the resilience quantification methods for both power systems and MESs. Review paper [24] focuses on the MLBTs applied to power system security and stability, especially the cyberattack detection, power quality disturbance studies and dynamic security assessment. Compared to the two review papers [9] and [24], we focus on MESs and resilience concepts, going further and addressing the following issues: *(i)* the concept of MES resilience and its relationship with security and stability, *(ii)* modeling and quantification methods of MES resilience, *(iii)* MLBTs applied to MES resilience assessment. In particular, the applications to MES network characteristics determination, prediction of system operation performance, and load curtailment prediction, *(iv)* MLBTs applied in academic and industrial projects, *(v)* future research directions on MES resilience quantification and assessment.

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 *(i)* the quantification methods of MES resilience, and *(ii)* 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. 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, is presented. The section is used as the basis for discussions in Section III and other Sections. The MES resilience modeling 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 agenda on MES resilience quantification and MLBTs applied to MES resilience assessment. Finally, conclusions are summarized in Section VI.

II. MES Resilience

A. Power system resilience definition

According to the IEEE Task Force [25], 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 [26], [27]. With the development of coupling technologies, concepts of digital substation and high speed communication, or distributed power systems, the interdependence of different energy sectors is stronger than before and the risk of unexpected disruptive, or cascading events is much higher [28]. Doors for propagation of disturbances from one to another energy sector are opened, which 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 sectors, but also network characteristics of different energy sectors under extreme events.

B. Conceptual relationship

The definitions of other relevant concepts, such as power system reliability, security and stability are known and can be found in e.g. [29], [30]. We briefly discuss here the relationship between the mentioned concepts, which is expected to more precisely define the paper scope. Reliability focuses on the system ability of uninterruptedly supplying customers, also during highly probable contingencies treated as N-1 or N-2 events. On the contrary, disruptive, extreme events are relevant for resilience assessment [31]. Security 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 different operating states [32]. In addition, normal, alert, emergency, extreme and restorative states are used to describe power system conditions [33]. Different resilience levels also correspond to these power system states [34]. 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: 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 [33]. On the other hand, power system resilience is an expression of the degree of the system capability to withstand a massive contingency, leading to simultaneous, or sequential outages, 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 [29]. A power system with vulnerabilities in the fuel supply can have fuel security problem [35]. Regarding flexibility, these are different definitions for a MES [36] and for power systems [37]. Both definitions focus on the ability to optimally manage the variability and uncertainty originating from the renewable power generation and loads. In [38], flexibility, together with resilience and connectivity, are perceived as the fundamental attributes of future sustainable power systems.

III. Modeling and Quantification of MES resilience

To assess the degree or the status of MES resilience, modeling 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 [39]. However, a review of the MES resilience quantification methods has not yet been fully addressed. MES resilience quantification methods can be classified into three groups: 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 [40] 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 have lasted before the restoration phase started and how quickly the resilience level degraded. To address these challenges, the *resilience trapezoid*, in [41] was proposed and applied to 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 state and 3) restorative state.

According to [25], 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, modeling is grouped by the performance of networks [42], system operation [43], and loads [44]–[46].

In [42], resilience r is modeled 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 sectors. The quantification method can indicate the effectiveness of energy flow influenced by the failure propagation between energy sectors through coupling system components. In [43] the system resilience r is modeled as the exponential of negative ratio of the increase in MES operation costs γ due to disruptive events, i.e.

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

where γ_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 [44], 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. However, the quantification methods mentioned above use deterministic-based modeling of disruptive events, not addressing the stochastic nature, e.g. probability, of the large-scale contingencies. In [45], the duration of phases II and III is modeled through the Monte Carlo Simulation (MCS) method, introducing the stochastic nature of the problem. In addition, for the purpose of MES modeling, the information about the disconnected load (load shedding) in all individual energy sectors, 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 [47].

Risk-based quantification methods have been traditionally applied in power system studies. In [48] the information about the vulnerability of electrical overhead transmission lines, modeled 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 [49] and [50], risk assessment frameworks for classifying the risk of failures in distribution and transmission networks were respectively proposed. In particular, the risk considered in [49] 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 [51]. However, in these studies the risk assessment methods applied to MES resilience problem are ignored.

In [52], a conceptual framework for developing resilience metrics of a 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 sectors needs to be normalized. Such a normalization method can make the resilience of different energy sectors 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 and the dimension reduction of scenarios from different sectors should also be considered.

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 [53] 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 [54], [55], 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 (edges connecting 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 [56]. The results indicate the system coupling amplifies the load curtailment caused by hurricanes. Furthermore, [57] 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 system operating 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 to power system reliability management has been comprehensively reviewed in [8]. Lots of attention has been put on static and dynamic security assessment and approaches for determining stability limits.

There are several terms from MLBTs [58] 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 an *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: *(i)* network characteristics determination, *(ii)* prediction of the system operation performance, and *(iii)* load curtailment prediction. Methods for resilience levels modeling and quantification are pre-discussed in Section III.

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 features, especially an interdependent network such as a MES. Here the resilience could be quantified by the topological features and graph-theoretical approaches discussed in Section III.C.

In [59], 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 [60]. 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

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

Ref.	System type	Event type	Resilience phase	Quantification metrics	Temporal/Spatial variations of resilience level	Resilience level model
[41]	E, transmission network	Windstorm, transmission line and tower failure	I - III	Resilience trapezoid	Temporal	Percentage of operational grid, generation and load
[42]	E, G, distribution network	Gas supply outage	I - III	Resilience trapezoid	Temporal/MES topology, contingency propagation between networks	Network efficiency
[43]	E, H, G, MES microgrid	Cyber threat, distribution line outage	II III	Resilience trapezoid and encryption cost	Temporal	Operation cost
[44]	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
[45]	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 sector
[48]	E, transmission network	Windstorm, overhead line outage	II	Risk assessment	– /Fault location	Vulnerability by fragility curve, probability of fault severity and windstorm occurrence
[49]	E, distribution network	Thunderstorm, lightning, windstorm, line outage	II	Risk assessment	Temporal/Network geographical information	Classification of risk, probability of failure and impact cost
[51]	E, distribution network	Lightening, distribution line outage	II III	Risk assessment	Temporal/Network geographical information	Classification of risk, probability of failure and impact cost
[52]	G, transmission network	Earthquake, gas pipeline and gas storage outage	II	Risk assessment	– /Fault location	CVaR
[56]	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
[57]	E, transport sector, 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

has no outcome measurements for resilience (labels). The resilience of all networks needs to be pre- or post-calculated by the quantification metrics. Reference [61] deployed a 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" [62] through the adjacency matrices. The resilience assessment of different types of network topology and coupling characteristics (coupling degree and order based on [63]) was then performed based on the energy supply for loads. However, the network topology and resilience variations in the propagation of contingencies were ignored.

Reference [64] further determined the sequence of the worst impact zones in the IEEE 123-node distribution network by the Q-learning algorithm. The propagation of line outage and generation loss caused by a hurricane was modeled, 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 [65], 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 ξ_{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 fact, the bias and variance of the prediction error obtained when using the FFNN method are respectively 0.43% and 50.7% less, leading to better model generalization to unseen scenarios. In [66], 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. The two proposed FFNNs have high accuracy of mean square error of 3.6×10^{-6} and 11.3×10^{-10}, respectively. On the other hand, as presented in [67], 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, with maximum 94.7% more accurate prediction of the security margin distribution.

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 [68]. Reference [69] 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 [70], the *decision tree depth* approach was used as the intepretability of decision tree methods applied to 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.

Other than supervised learning methods, the unsupervised learning methods are also applied to predict the system operation performance. The association rule learning, an unsupervised learning method, can identify the frequent patterns in data sets where joint values of features appear. The method was adopted in [71] to find the association rules between different types of faults in distribution systems and the conditions leading to the faults. The association rules generated by the Apriori algorithm are qualified and ranked by the measures of *support, confidence* and *lift*. The top-ranked rules with high *lift* values are selected in [71], as frequent patterns of different faults occurring in distribution systems. The association rule learning method is also applied to a MES of heating, gas and electricity in [72], to predict the risks of transmission line faults considering different periods, locations, weather, voltage levels, etc.

Besides the system security states, the operation cost is also quantified for resilience assessment, which has been modeled and used to quantify the MES resilience in Section III.A. In [73], the restoration actions of dispatching the restoring power are determined by a proposed 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, [74] 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 to direct prediction of the system performance under contingencies from the system operation perspective. In [75], 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 99% higher prediction accuracy both referred to the piece-wise linear benchmark method. 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 operating 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. The modeling of the loss of load to quantify the MES resilience has been discussed in Section III.A. 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 to the load curtailment prediction are discussed.

In [76], 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 [77] 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 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

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	[60]
	CNN	Reduce feature dimensions and measure similarities among nodes	[60]
		Classification of integrated power and gas networks	[61]
	Reinforcement learning	Determine the sequence of outage propagation	[64]
	Linear regression	Relations between electrical network features and system resilience	[59]
Prediction of system operation performance	FFNN	Operation costs	[65]
		Line flow and bus voltage	[66]
		Power system security margin	[67]
		Classification of safe/unsafe operation (violation of generator and line limits)	[69]
		Energy flow of power and gas	[75]
	Decision trees	Classification of safe/unsafe operation (violation of phase angles and internal voltage of generators limits)	[70]
	Association rule learning	Identify and rank frequent patterns of different faults occurring in systems and fault conditions	[71], [72]
Load curtailment prediction	Autoencoders	Feature extraction for better classification by a classifier	[76]
	Decision trees	Classification of safe/unsafe operation (load curtailment)	[76]
	SVM	Decision making of preventive actions for minimum expected load not supplied	[77]

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 [76], 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.

D. MES resilience enhancement

The resilience enhancement can be achieved through enhancement actions in the three phases mentioned in Section III.A, disturbance progress, post-disturbance state and restorative state. The MLBTs applied to phase III, restorative state, through restoration actions are shown in Table III. Reinforcement learning methods are mainly utilized to make fast and sequential decisions for restoration actions. The resilience levels are quantified by methods discussed in Section III. The decision-making of the restoration actions is made through reinforcement learning, such as transportation routing and scheduling [78], reconfiguration of switches [79] and DER control [80]. Furthermore, a coordination of DERs dispatch and mobile energy storage scheduling was proposed through DRL in [81]. The coordinated operation can enhance the distribution system resilience by restoration of critical loads in the microgrids. In [82], neural networks are modeled to generate the worst-case conditions of loads and wind power generation, and the security assessment. The MLBTs can also be applied to the system in normal operating state by enhancing the forecasting of extreme events. The relevant literature is shown in the new Table IV. The forecasting methods are used to predict the power demand and production, component outages, and supply interruptions considering extreme weather conditions. Then the prediction is used for preventive actions to prepare for the extreme event occurrence in [83], [84].

E. MLBTs applied in academic and industrial projects

A table of MLBTs applied in academic research projects is shown in Table V. These projects started in recent years or will be initiated in the near future, and cover the application to power system resilience assessment [87], MES resilience enhancement [88], [89] and MES resilience assessment [90]. However, some MLBTs, e.g. deep neural networks, require a large volume of data for training the model, which is not always available for a resilience problem dealing with extreme events. In [87], a combined MLBTs and physics-based approach is proposed for system operators to detect and classify faults in those extreme events. The additional information obtained from mathematical physics models to the measurement data, i.e. physics-informed machine learning, can improve the accuracy, training time and generalization of MLBTs [91]. In these projects, the effectiveness of the MLBTs is always justified through simulated test systems, due to the limitation of testing contingencies on real-life systems.

In addition, there are also real-life projects implemented by industry. A table of MLBTs applied in real life by industry is shown in Table VI. Here the main applications include the prediction/assessment of the system performance in real-life low-voltage power systems, such as fault detection through neural networks [92] and classification [93]. In addition, network characteristics determination is applied to identify the geographical information of the fault for fault management [93]. For transmission systems, classification, regression and clustering methods are used to automatically detect and prioritize the large volume data for notifying control rooms. Such methods can support the decision-making of correction actions at source [94]. The methods are validated against historical data provided by the control room. However, it is still under investigation to implement the resilience enhancement actions in real-life large-scale transmission systems. The

TABLE III
MLBTS APPLIED TO RESTORATION ACTIONS FOR RESILIENCE ENHANCEMENT

Learning type		Energy system	Resilience level model	Enhancement action	Ref.
Reinforcement learning	Multi-agent reinforcement learning	Transportation and power systems, distribution level	Loss of load and electricity import cost from main grid	Routing and scheduling electric vehicles for power system restoration	[78]
Reinforcement learning	DRL	Power systems, distribution level	System performance and loss of load	Decision-making of restoration action: reconfiguration of distribution switches, transformer tap-changer operation, and interconnection of a microgrid with the main grid	[79]
Reinforcement learning	Q-learning	Power systems, microgrids	System performance at the point of common coupling	Dispatchable DER control and interconnection to microgrids	[80]
Reinforcement learning	Q-learning	Power systems, transport systems, distribution level	System operation cost	DERs dispatch and mobile energy storage scheduling	[81]
Neural networks	CNN	Power systems, transmission level	Load recovery level	Decision-making of load restoration under worst case scenario	[82]

TABLE IV
MLBTS APPLIED TO FORECASTING FOR RESILIENCE ENHANCEMENT

Learning type		Forecasting extreme event	Enhancement action	Ref.
Unsupervised learning Supervised learning	Clustering Random Forest, Light Gradient Boosting Machine	Probability of power system interruption based on the prediction of microgrid load demand, solar production and supply interruption probability considering weather conditions	Day-ahead generating units rescheduling	[83]
Supervised learning	CNN LSTM	PV production considering historical power output, power consumption and weather conditions	—	[85]
Supervised learning	Bayes Classifier	Power system component outages in extreme weather events	Preventive actions, rescheduling of generating units	[84]
Supervised learning	Linear regression, SVM, Neural Networks	Electricity demand considering extreme weather conditions	—	[86]

TABLE V
MLBTS APPLICATION IN ACADEMIC PROJECTS RELATED TO MES RESILIENCE

Project name/Country	Resilience quantification/ assessment/enhancement	MLBTs	Simulation system/Demonstration
Detection, characterization, and mitigation of disruptive events by combining machine learning/ artificial intelligence on synchrophasors and physics-based analysis, US [87]	Detect and classify faults, oscillations, impending instability, and other events that may lead to system emergencies	Supervised and unsupervised learning; Combined MLBTs and physics-based solutions	Upcoming project
NetworkPlus - A green, connected and prosperous Britain, UK [88]	Power system and 5G telecommunication network recovery with real-time control of electric vehicles as mobile energy storage	DRL	Demonstration of MLBTs applied to 5G telecommunication link routing
Technology Transformation to Support Flexible and Resilient Local Energy Systems, UK [89]	Local control of electric vehicles and DERs to provide resilience to component failures in power systems	DRL	Test MES of electricity and transport
Disaster REsilience Assessment, Modeling, and INnovation, Singapore [90]	Resilience prediction of an urban MES of power, water and transport. Correlation identification between different system features and the resilience levels	Interpretable machine learning methods	City MES in Southeast Asia against weather-related disasters

French transmission system operator RTE with Electric Power Research Institute (EPRI) initiated the L2RPN (Learning to Run a Power Network) Challenge platform to build trust between the decision-making by MLBTs and the operator in a control center [95]. In the platform, reinforcement learning methods were proposed by [96] to overcome the computation and scalability concerns of resilience enhancement in transmission systems and tested in IEEE test systems.

V. FUTURE RESEARCH AGENDA

In this section, the most relevant research questions related to *(i)* modeling and quantification of MES resilience and *(ii)* application of MLBTs to 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 sectors be combined to assess the overall system resilience?

TABLE VI
MLBTS APPLICATION IN INDUSTRIAL PROJECTS RELATED TO MES RESILIENCE

Company/Utility	Real-world application	MLBTs	Effectiveness of MLBTs
Fundamentals, power system technology specialist, UK [92]	Detection, classification and location of low-voltage fault	Physics-based deep learning	Test fault in low voltage underground cables at the Power Network Demonstration Center, UK
EA Technology, power system asset specialist, UK [93]	Detect, localize and locate low-voltage fault	Classification	On site verification of accurate fault location and fault management
Harmonic Analytics, data science company, New Zealand [94]	A visual tool for transmission system alarm management: identify, analyze and prioritize control room alarm data	Classification, regression and clustering	Reduction in alarm volumes, improved operational efficiency and proactive asset management
RTE, French transmission system operator and EPRI, US research institute [95]	Secure operation of power systems at low cost conducted on IEEE-118 test network	Reinforcement learning	Continuously and safely control a power grid to maximize available transfer capabilities without operator's intervention [96]
6 European Transmission system operators, Innovative Tools for Electrical System Security within Large Areas (ITESLA) project [97]	ITESLA toolbox for online security assessment	Principal component analysis and decision trees	Simulation tests on French transmission network to validate the security rules
General Electric (GE) Digital [98]	STORM software tool for real-time outage detection and decision support for reliable operation during extreme events	MLBTs embedded in digital twins	Pilot tests for grid operation during wildfire seasons in California

2) How can the MES resilience be quantified when component failures occurring in different energy sectors 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 sector?
4) How is the MES resilience level changed with the contingency propagation through different energy sectors? 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 secure communication [99] infrastructure could contribute to the system resilience?
6) What would be the cost of the design of advanced SIPS for boosting system resilience?

The resilience of each energy sector is traditionally monitored and quantified within the sector in question. Resulting from the mutual coupling, the resilience levels of individual sectors are correlated to each other in terms of time, contingency location and intensity. The awareness of other sectors' 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 sectors for quantification of the overall MES resilience.
2) Modeling of joint probability distribution of two simultaneous outages occurring in different energy sectors 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 sector.
4) Consideration of different speeds of the propagation of cascading failures in different energy sectors.
5) Assessment of communication networks and data analytics for resilient MES [100]. 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 challenging in 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 sectors are integrated into a single MES through the coupling technologies/units, such as gas compressors, electric heating units and CHP plants. Meanwhile in Fig. 2, the resilience trapezoid in [41] is extended with the resilience level varying in the location in the network (e.g. nodes) as well as energy sectors. The resilience level of each energy sector 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 sectors 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 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.

There are also some challenges with implementing MLBTs in MES resilience assessment and enhancement:

1) High dimensional features from all energy sectors. Therefore, feature extraction or selection techniques need to be adopted for further resilience prediction and classification.
2) Not enough historical operational data of the system under extreme events, due to their low probability nature. In addition, due to the high integration of converter-interfaced generation and RESs, the uncertainty of power generation requires a much larger data to cover the uncertain scenarios and the corresponding resilience level. These data are required to train some machine learning models, e.g. neural networks.
3) Lack of data can lead to imbalance data/classes and inaccurate classification prediction. Therefore, new sampling and data augmentation methods are needed to enrich the minority class and eventually improve prediction accuracy.
4) Large-scale MES with many possible actions such as load shedding of different energy sectors could make the DRL not efficient.
5) Verification of machine learning model. It is difficult for the user (e.g. a system operator) to trust the MLBTs, to apply them to assess the MES resilience, and finally to take actions to enhance the resilience.
6) Demonstration of machine learning models in real life is still limited, especially the application to MESs. Though there are several relevant projects shown in Tables V and VI, the MLBTs applied to MES resilience are not yet demonstrated in a large-scale energy system.

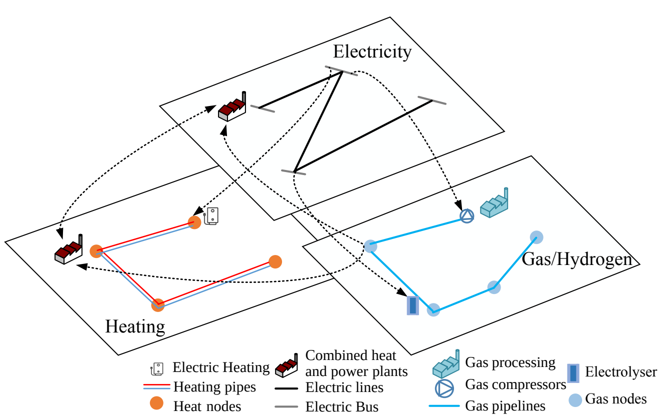

Fig. 1. A MES of electricity, heating and gas/hydrogen sectors integrated with coupling technologies

There are also some opportunities with the MLBTs applied to MES resilience:

1) The MLBTs have the advantages of detecting outliers from a large data set automatically and fast, which do not follow the patterns of normal operation. They can explore millions of system contingencies and operating states to train machine learning methods offline. The methods are then used to identify the system resilience level and distill the results in security rules applied in real time [101].
2) There are not yet sufficient applications of MLBTs to resilience assessment in other energy sectors, e.g. district heating and natural gas. There is existing literature on heat load prediction at critical nodes (nodes furthest from the heating supply), and uncertainty propagation in gas networks through gas pressure variance [102]. However, the MLBTs applied in these energy sectors in extreme events are not fully explored.
3) The digital twin concept, a virtual replica of a physical MES, enables testing and experimenting the impact of integration of new technology and strategy [103]. The MLBTs can be embedded in the digital twin to simulate the MES operation in various extreme events, and to develop and verify the resilience assessment and enhancement methods. The methods can support the real-time operation of the MES.

Consequently, the following research directions are identified:

1) Application of MLBTs, e.g. DRL, for determining failure propagation sequences in a 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 im-

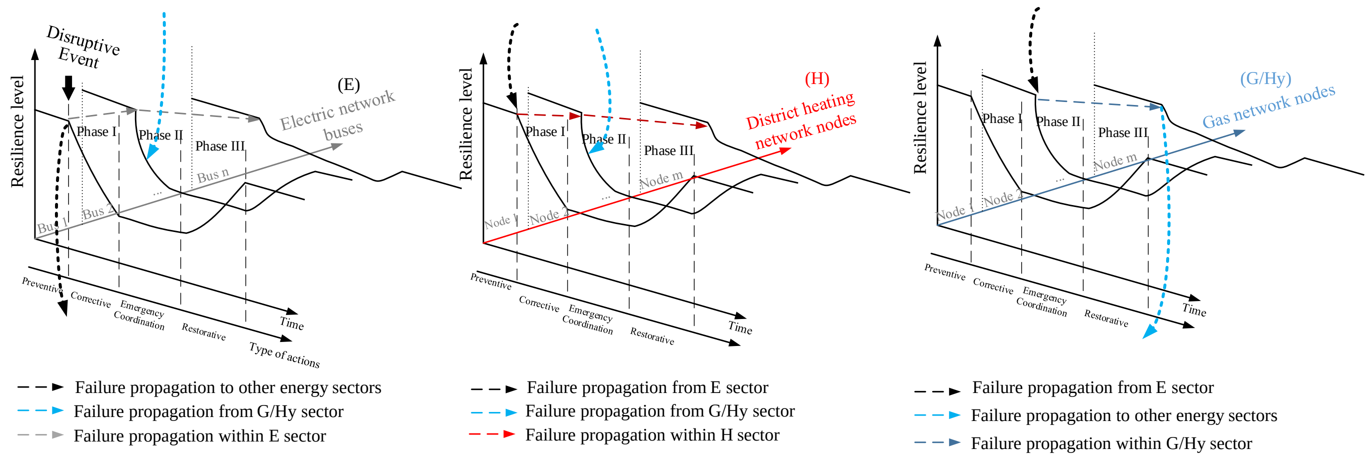

Fig. 2. Resilience trapezoids of individual energy sectors (electricity (E), heating (H) and gas/hydrogen (G/Hy)) under disruptive events

proving 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.
7) Development of physics-informed machine learning methods which integrate the historical data and physical laws of a MES. This can make the MES resilience level prediction more accurate while requiring fewer training data.
8) Development of methodologies to verify the performance of MLBTs and to quantify their trustworthiness and robustness against uncertain extreme events.
9) Implementation of hardware-in-the-loop tests for validating and demonstrating new MLBTs-based concepts for enhancing MES resilience in real time.
10) Simulation of a large number of scenarios through digital twins embedded with MLBTs. Such a digital twin can make more informed decisions in MES resilience assessment and enhancement under different extreme events.
11) Consideration of the information and communication technology (ICT) infrastructure connected to the MES during extreme events. The ICT infrastructure couples the information/data/control signals and the physical units in a MES. Outages of power systems can lead to the outages of ICT infrastructure, e.g. base stations, leading to the loss of telecommunication networks. Mobile energy storage such as electric vehicles can contribute to the recovery of ICT infrastructure therefore enhance the whole 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 modeling 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 the last two sections, the MLBTs applied to MES resilience enhancement, academic and industrial projects on this topic are discussed.

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 sectors are needed, Group 2): the probability distributions of the consequences on each energy sector from the same event are always correlated, and Group 3) the spatial information of different energy sectors 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 are 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 low 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.

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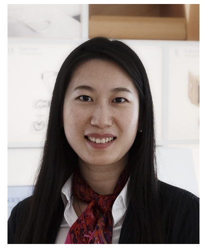

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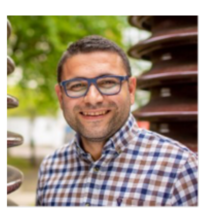

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