Adaptive Fault Detection Scheme Using an Optimized Self-healing Ensemble Machine Learning Algorithm

Levent Yavuz, *Student Member*, *IEEE*, Ahmet Soran, *Member*, *IEEE*, Ahmet Önen, *Member*, *IEEE*, Xiangjun Li, *Senior Member*, *IEEE*, and S. M. Muyeen, *Senior Member*, *IEEE*

***Abstract*—This paper proposes a new cost-efficient, adaptive, and self-healing algorithm in real time that detects faults in a short period with high accuracy, even in the situations when it is difficult to detect. Rather than using traditional machine learning (ML) algorithms or hybrid signal processing techniques, a new framework based on an optimization enabled weighted ensemble method is developed that combines essential ML algorithms. In the proposed method, the system will select and compound appropriate ML algorithms based on Particle Swarm Optimization (PSO) weights. For this purpose, power system failures are simulated by using the PSCAD-Python co-simulation. One of the salient features of this study is that the proposed solution works on real-time raw data without using any pre-computational techniques or pre-stored information. Therefore, the proposed technique will be able to work on different systems, topologies, or data collections. The proposed fault detection technique is validated by using PSCAD-Python co-simulation on a modified and standard IEEE-14 and standard IEEE-39 bus considering network faults which are difficult to detect.**

***Index Terms*—Decision tree (DT), ensemble machine learning algorithm, fault detection, islanding operation, k-Nearest Neighbor (kNN), linear discriminant analysis (LDA), logistic regression (LR), Naïve Bayes (NB), self-healing algorithm.**

I. INTRODUCTION

THE rapid growth of energy consumption throughout the world brings new technologies together in power systems. In addition to traditional systems for energy generation, such smaller on-site power generating platforms, (e.g., wind turbines or other renewable energy systems), have emerged recently. Distributed Energy Resources (DER) arouses new investment areas, such as Microgrids or Virtual Power Plants, that surely attract people looking for possible business opportunities.

However, using a set of different renewable systems needs to be coordinated and/or controlled by small units, such as hardware supported Microgrids or pure communication enabled software-based Virtual Power Plants. A microgrid, a localized remotely controllable and self-operating group of energy sources, uses a type of controller that may operate in grid-connected or islanded modes to dispatch energy [1].

More importantly, increasing more renewable penetrations reduces rotating inertia. For example, the total inertia currently available in the South Australia network is around 16,200 MWs. In 2017, without the Northern Power Station and Torrens Island "A" Power Station, the total available inertia would reduce to around 10,000 MWs [2] due to the inclusions of renewable sources, which is very alarming. This may cause system instability or even a blackout, in case of catastrophic events or grid fault conditions [3], [4] and faults are needed to be cleared quickly. Therefore, special precautions must be taken to avoid any greater outage and/or cascading blackouts. Considering these, many fault detection techniques have been developed recently and reported in power system literature [5], [6].

In the traditional power system, primarily the protective relay receives the voltage, current, and frequency information from transmission/distribution systems using instrumentation transformers. That information is typically processed by the protective relay to take action in case of emergency or abnormal conditions for the desired tripping time. The relay logic algorithm takes the decision of whether to trip open or to close the circuit breaker. In the distribution system, the protective relays require a large fault current to detect the faulty condition. This is problematic for the modern distribution system which connects various Distributed Generations (DGs) including renewable sources, microgrids, and virtual power plants. Most of the DGs, nowadays, are equipped with inverter technology which typically contributes at two times of per unit rated current, as rule of thumb [7]. This is troublesome because the current level may not be sufficient to trigger the relaying action and it puts the inverter equipped modern distribution system at risk.

Many fault detection mechanisms have been depicted in the

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L. Yavuz and A. Soran are with the Electrical and Computer Engineering Department in Abdullah Gül University, Kayseri 38080, Turkey.

A. Önen (corresponding author, e-mail: a.onen@squ.edu.om; ORCID: https://orcid.org/0000-0001-7086-5112) is with Department of Electrical and Computer Engineering, College of Engineering, Sultan Qaboos University, Al-Khoud, Muscat, 123, Oman.

S. M. Muyeen is with the Department of Electrical Engineering, Qatar University, Doha 2713, Qatar.

X. J. Li is with State Key Laboratory of Control and Operation of Renewable Energy and Storage Systems, China Electric Power Research Institute, Beijing 100192, China.

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power system. The real-time data acquisition device like Frequency Disturbance Recorder (FDR), optimally placed Phasor Measurement Units (PMUs), and many other equipments are used to detect power system faults [8]. Line outage detection using phasor angle measurements are reported in [9]. Fault detection occurred in DC and AC microgrids are reported in [10]. One of the methods could be using additional equipment(s) to build a protection layer for renewable source integrated microgrid; however, this requires additional hardware cost [5]. Besides, the faulty equipment is required to be fixed or replaced in the case of equipment failures, which adds more cost and labor. It is noted that equipment failures are frequent events and blackouts are mostly triggered by these problems. Apparently, hardware-based applications seem not scalable and they are infeasible due to financial problems. Thus, many new intelligent computer-aided prediction techniques have been developed to deal with fault scanning [11]–[13].

In recent years, many soft computing and data-driven approaches have been investigated to detect power system faults. The performance of these techniques can be measured by (i) the rate of their accuracy, (ii) detection time, (iii) cost-efficiency, and (iv) flexibility/adaptivity.

i. There are various methods proposed to achieve the highest accuracy rates, i.e., deciding islanding operation correctly. Primarily, hybrid techniques [14], applying suitable threshold settings [15], and signal processing techniques [16], [17] have been proposed. Traditional fault detection systems, signal processing methods, threshold settings, and their deficiencies are detailed in Section II.
ii. The proposed methods should be fast enough for detecting the faults over the network. There is a tradeoff between accuracy and detectiontime. In the experiments, we were challenged by IEEE 1547 standards [18], which require the detection of possible faults within 2 seconds at the most, and attempted to obtain better results of up to 0.021 seconds. Computational time is almost 1% of IEEE standards.
iii. While adding new components to the DER systems, we need to keep the system practical and feasible at the same time. If renewable applications become wide-spread, energy marketing would become higher than ever [19]. Therefore, the fault detection module must be cost-efficient for the new applications.
iv. DER systems gather various renewable energy resources together and create a gigantic heterogeneous environment, which requires practical solutions to manage the whole network. This is because, especially increasing PV farms on the network, it brings voltage and frequency deviations together [20], [21]. These deviations make the power system unstable, and so it must be eliminated by using different techniques. Consequently, fault detection methods can cause a mistake because of these fluctuations. Although there are no faulty conditions, transmission system operator's devices or some algorithms could decide wrong decisions [22]. Then, the proposed fault detection algorithms should also be scalable and adaptive for any type of power systems with a different number of buses. We observed that many proposed algorithms are designed for the static power system topologies that do not change frequently. In the case of modifying the network by adding/dropping a line or adding new buses, most of the proposed algorithms may fail.

In order to create a new intelligence-based fault detection method, we consider all these metrics. Different solutions use only one machine-learning algorithm to reach the time goal or use complex ones that merge multi-machine learning algorithms to obtain higher accuracy results.

The proposed method combines different ML algorithms which are called weak-learners. Particle Swarm Optimization (PSO) is used for this combination process in this study. Optimum weights are calculated and given a set of weak-learners in order to reach higher performance together. By using this approach, each weak-learners weakest part is closed by others. Behind the power of the proposed method is the ensebmling technique. The main idea is to calculate the almost ideal weights for each machine learning algorithm periodically and then combine them with soft voting during the test conditions. With this adaptive technique, we improve both the accuracy rate and time while only increasing training time by a little bit.

Signal processing approaches, such as decision tree and random forest, are extensively utilized to detect the fault in distribution systems connecting microgrids [23]. There are also some other signal processing approaches: Fourier Transform, Wavelet Transform, S-Transform, TT- Transform, and Hilbert Huang Transform techniques have successfully been applied to detect faulty conditions [4], [24], [25]. Data-driven approaches have also received attention by power system researchers in identifying faults [26]. The Machine learning technique requires the computer/system learn various patterns based on the given input and hence it is found applicible for power system fault detection [27]. For instance, the machine learning algorithms, such as the k-Nearest Neighbors (kNN) algorithm, support vector machine, etc., are adopted in identifying grid faults [28], [29].

It is noted that the inclusion of renewable sources causes frequent voltage and frequency fluctuations [20], [21] which may cause power system vulnerabilities, making fault detection methods unreliable. Although there are no fault conditions, the protection devices or fault detection algorithms may receive erroneous signals from those random voltage and frequency fluctuations [22]. Therefore, the fault detection algorithms should also be scalable and adaptive when renewables penetration increases. It is also observed that many algorithms are designed for the static power system [30] and in the case of network alterations by adding/dropping a line or adding new buses, most of the proposed algorithms may fail, so the systems have to be adaptive.

Considering the aforementioned issues, a real-time fault detection technique is developed in this study using an optimization enabled weighted ensemble based Machine Learning Algorithm. The proposed method is simple to implement as it uses voltage, frequency and phase angle signals obtained from PMUs.

There are different solutions that use only one Machine Learning (ML) algorithm to reach the time goal [24], or complex ones that merge multi-machine learning algorithms [25], [26] to obtain higher accuracy results. The proposed method, in this study, is a type of ensembling type blending optimization algorithm where the Particle Swarm Optimization (PSO) finds the optimum weights to eliminate the forecast errors coming from each ML algorithm. Another rigid contribution of this method that can be used is that the system exhibits flexible / adaptable behaviors as a result of any change. As commonly known, power systems exhibit a constantly changing/ changeable structure. Algorithm-based error detection systems may not be able to adapt to these variations. Such problems are frequently encountered, especially in methods developed by detecting the threshold. The Cross-validation method has been used to eliminate the overfitting problem. When the accuracy reaches 100%, the algorithm is memorizing the data set, named overfitting. This is one of the prevalent problems in the machine learning field.

For most of this study, we used the overfitting technique, which comes from memorization of results instead of learning, and causes you to unrealisticlly reach a 100% accuracy rate. This is due to ignoring cross validation techniques that are taken into consideration in this study to be able to represent results in a real world power system environment.

The rest of the paper is organized as follows. Section II discusses machine learning algorithms used in fault detection and their mathematical algorithmic background is represented. The ensemble and boosting algorithms are discussed in Section III. In Section IV, the proposed algorithm architecture is presented. Effectiveness and success of the proposed algorithm by comparing with individual ML algorithms and Ensemble methods are represented in Section V. Finally, findings of the proposed study are summarized in Section VI.

II. Iterative Machine Learning Algorithms in Fault Detection

ML applications are not computer programming, like traditional computer algorithms. ML creates a special algorithm for a given data/situation which exactly fits the system.

In the power system, researchers are faced with different problems that are very close to the needed ML applications. Power transmission and distribution problems depend on too many variable states. A faulty condition could be happening on transmission and distribution lines, for example; a bird/snake can touch the cable, or a tree can fall down on the transmission/distribution line, causing a short circuit. Since it is very difficult to encounter that these typess of faulty situations on a regular basis, the training data set may need to be generated via simulations. Then, the ML technique could be an effective way to detect these faults. When hardware-based solutions can not entirely handle these problems, ML creates a special algorithm for a given data/situation which exactly fits the system. Some of the ML techniques which can be used in signal processing and fault detection are presented as follows.

A. Machine Learning Algorithms

1) k-Nearest Neighbor (kNN)

The kNN is easy to apply, and is a simple and effective algorithm for binary or multi-classification problems. It considers the set of observation data and checks the neighbors of the new incoming items according to the value of k, the number of neighbors. In most of the ML applications, the k value is chosen as a default 3 or 5, and also the Minkowski distance (1) is chosen as a distance length metric. The process of the algorithm is simple; according to the number of neighbors and the coordinates of the new data $(x_1, y_1), \cdots, (x_n, y_n)$, the k's nearest neighbors are determined by measuring the distance, e.g., Euclidean distance, Minkowski distance or Manhattan distance, for all of the newcomers, and finally the system decides the clusters of the new nodes with the closest distance [33].

$$d(x, y) = \left(\sum_{i=1}^{\mathrm{n}} |(x_i - y_i)^p| \right)^{\frac{1}{p}} \tag{1}$$

2) Linear Discriminant Analysis (LDA)

Linear Discriminant Analysis (LDA) can be used to reduce the size, improve computational efficiency, and reduce overfitting in non-digitized models. The LDA is very similar to Principal Component Analysis (PCA). The PCA tries to find the orthogonal component axis of the maximum variance in a data set; The LDA tries to find the feature subspace that optimizes class separability. The LDA and the PCA are linear transformation techniques that can be used to reduce the number of dimensions in a dataset.

The present state of the dataset is used to make the data more easily separable when it is not very convenient to separate the components. To achieve this, it also takes advantage of the covariance matrix. In fact, it is not literally a classification algorithm. It can be used as a pretreatment before the classification process when there is not enough differences to distinguish the classes following the feature extraction. To distinguish between classes, LDA examines the distribution of classes and uses the difference between the average values.

3) Logistic Regression (LR)

Logistic regression is a statistical method used to analyze a dataset with one or more independent variables that determine a result. The result is measured by a binary variable (there are only two possible results). In logistic regression, the dependent variables must only be binary. In nother words, final results are only 1 (TRUE, success, etc.) or 0 (FALSE, error, etc.) as encoded data.

The purpose of logistic regression is to find the most appropriate (yet biologically plausible) model to define the relationship between a number of independent (predictive or explanatory) variables related to the two-way characteristic variable (dependent variable = response or outcome variable). Logistic regression produces the coefficients of a formula to estimate the probability.

4) Naïve Bayes (NB)

The algorithm has been widely studied since 1950, based on the Bayes Theorem and it uses the idea of the simple probabilistic classifier. In statistic and computer science, the NB is represented as conditional probability [31]. Terminologically, the Bayesian probability is given in (2).

$$p(C_k|x) = \frac{p(C_k)p(x|C_k)}{p(x)} \tag{2a}$$

$$\text{posterior} = \frac{\text{prior } x \text{ likelihood}}{\text{evidence}} \tag{2b}$$

where $p(C_k|x)$ is the posterior probability of class, $p(C_k)$ is the prior probability of class, $p(x|C_k)$ is the likelihood, $P(x)$ is evidence.

5) Decision Tree (DT)

In Machine Learning applications, the Decision Tree (DT) is one of the most preferred algorithms due to its simplicity. The DT gives all possible outcomes and if you have enough data for the next future prediction, it can decide precisely. The DT uses a math-based background that relies on Shannon Information Theory and entropy calculations [34]. The biggest entropy value is the start of branches and the whole tree follows it with the same scheme as shown below:

$$E(s) = \sum_{i=1}^{c} -p_i \log 2(p_i) \tag{3}$$

where $E(s)$ is entropy and it represents the power and dominancy of the feature frequency. Therefore, the branch starts from the feature which has the biggest $E(s)$ value; p_i is the probability.

B. Finding Best Decision Variable for Each ML Algorithms

Machine learning algorithms require several parameters that can affect the accuracy rate. Before bagging several ML techniques as an ensemble algorithm, in order to understand the optimum parameters of each algorithm, the proposed method checks the sub-set of parameters or decision variables given in Table I (unshaded part). The ML algorithms were run iteratively with different parameters and the best combination is obtained for a given algorithm as demonstrated in Fig. 1. This code cycle is processed for just one time until the power system or data structure changes. The main idea of this loop is to obtain the best decision variables for the PSO optimization based Ensemble algorithm shown in Section IV. Briefly, the PSO-based Ensemble algorithm combines different iterative ML techniques with the best parameters and weights. Since chosen ML techniques for the bagging process will always use the same local parameters during the decision time span, optimum parameters are obtained individually with this looping process before continuing with the optimization part. Since the power system structure is not always kept constant and requires some changes over time, algorithms need to be able to work with updated network structures. This ability is known as the self-healing property of algorithms that ensures the detection and update of decision variables and weights when power system structures are changed.

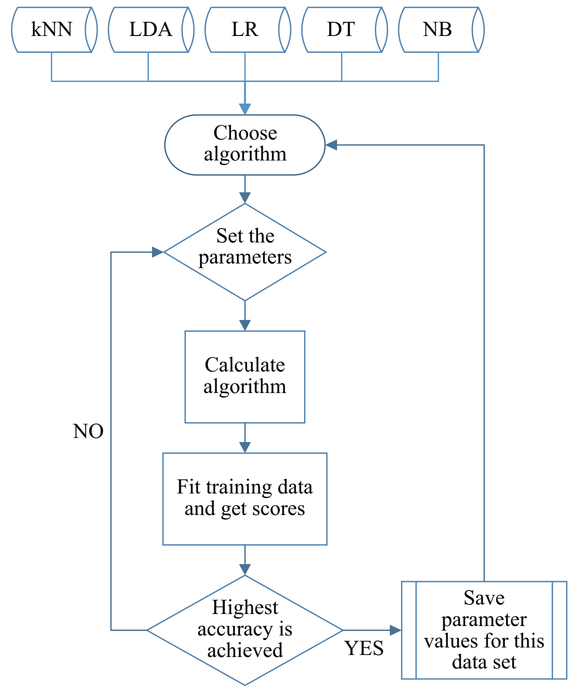

Fig. 1. Tuning the parameters with grid search to calculate the best decision value for each ML Algortihm.

For instance, when kNN is working, the algorithm checks the k neighbor value to find the best decision variable that provides the maximum accuracy rate for a given dataset. Although these parameters can be altered with topological changes, this proposed approach finds new values before applying the optimization algorithm. Thus, the system becomes robust and adaptive with various datasets.

TABLE I
PARAMETERS TO CALCULATE THE DECISION VARIABLES FOR SELECTED ML AND ENSEMBLE ALGORITHMS

ML and Ensemble Algorithms	Decision Variables	Interval
kNN	number of neighbors	[3 to 21, incremented by 1] (Testing results gives that k must be 9 for that dataset to obtain highest accuracy result)
LDA	tolerance	0.0001
LR	–	–
DT	–	–
NB	–	–
Gradient Boosting and Adaboost algorithms are also tunned for comparison with proposed method.		
AB	Estimator	[1 to 100, incremented by 5] SAMME, SAMME.R
GB	number of trees	[11 to 71, incremented by 1]
	seed	[1 to 11, incremented by 1]

III. ENSEMBLE ALGORITHMS

Ensemble methods refer to combining weak learning algorithms and transforming them into a strong learner with additional processes. Weak learners can work sequentially, and each predictor tries to fix the previous results via the boosting method. The other approach is to combine the results of weak learners with the bagging method. So, ensemble techniques can be applied with a feedback mechanism, such as Adaboost and Gradient Boosting, or it can be a vote-based method, such as the bagging approach. So the boosting algorithms work as ensembling methods.

A. Bagging Methods

(i) *Majority/Hard voting* is a simple case of voting methods with a voting algorithm which is given in (4).

$$\forall C \in \text{Cn} \tag{4a}$$

$$\varphi = \text{mode}\{C_1(x), C_2(x), C_3(x), \cdots, C_N(x)\} \tag{4b}$$

$$\begin{pmatrix} C_1(x) \\ C_2(x) \\ \vdots \\ C_N(x) \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ \vdots \\ 1 \end{pmatrix} \tag{4c}$$

$$\varphi = \text{mode}\{0, \cdots, 1\} = 0 \text{ or } 1 \tag{4d}$$

where φ is the final decision of total results and it uses the Python's mode command. This is a piece of code cycle; $C_1, C_2, \cdots, C_N$ are the classifier's decision results, either 0 or 1.

In this scheme, each ML algorithm comes up with the decision on the given test case, separately. The final decision will be given with the agreement of the majority.

(ii) *Soft voting* gives the average probability of the decisions rather than counting the votes on positive or negative decisions coming from the ML algorithms. For example, when three algorithms give the decisions with (0.60, 0.60, 0.15), then hard voting will decide negatively, since there are 2 positives and one negative. However, the soft voting will decide it as being negative due to the average of the probability which is 0.45. In this example, algorithms have the same significance, however, the weights can be different if the contribution of the algorithms is not the same.

B. Boosting Methods

AdaBoost (AB) iteratively repeats the weak learner algorithm with given instances. In each iteration, misclassified data items are re-weighted according to the information gained from the previous step. With this feedback mechanism, the AB runs a classifier, changes the weights, runs another classifier, and repeats until most of the items are classified properly. Thus, there is no parallel calculation, each step must follow the previous ones, just like a chain.

The Bagging and boosting processes are represented in Fig. 2. Not only does the bagging process preceed the boosting type but it also is reinforced with PSO that results in faster processing time when compared with any other ML algorithm or boosting method.

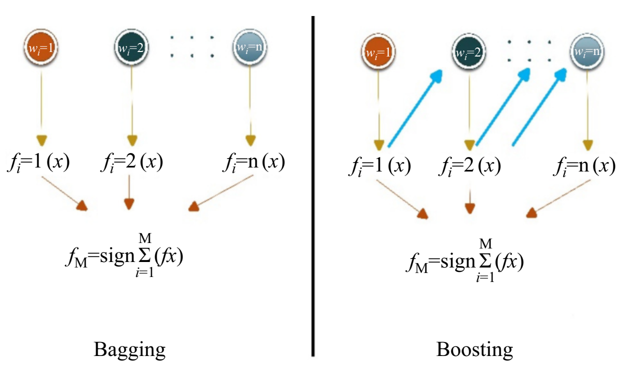

Fig. 2. Bagging and boosting methods.

Gradient Boosting (GB) also combines multiple ML algorithms based on weights. It collects weak learners and makes a new stronger learner and works as a team. A dataset is applied to this algorithm in order to obtain the best result. The GB has 2 types of algorithms; one of them is SAMME.R and the other one is SAMME. Each algorithm's decision variable values are listed in Table I (shaded part).

IV. Proposed PSO based Weighted Ensemble Approach

The workflow for the proposed algorithm is shown in Fig. 3 which combines five different ML algorithms explained in Section III, by using a novel weighted ensemble approach blended with the Particle Swarm Optimization (PSO) technique to accurately detect the faults on the power system. The proposed approach is explained by the following steps:

1) Collect the data from the sensors and all other parts of the system, e.g. SCADA, to train the system periodically.
2) For each ML algorithm, the best decision variables of the techniques are calculated with the Brute-Force approach as shown in Section III.B.
3) The weights of ML algorithms for the bagging process, which are based on the soft-voting technique, are calculated by Particle Swarm Optimization module. Thus, PSO will give the best set of weights for the soft-voting approach. During this process, bagging is applied with the PSO calculated optimized weights until the next training time window.
4) The ensembling process uses a minimum 2 and maximum 5 ML algorithms according to PSO results. In this process, cross validation was applied to the dataset to evaluate the predictive performance of the model results in the training dataset step. In applying this approach, one of the well-known methods, K-Fold Cross Validation (cv), is applied as cv=5. That means, 80% of data was chosen for the training part and 20% of data was for testing purposes.
5) A self-healing algorithm has been developed which is adaptive against the structural changes and the algorithm collects the data and controls the power system in case of any faults. Based on each of the algorithm weights obtained in step-4, the power system control action is triggered, in this case, in a PSCAD simulator.
6) If structural changes occur, the proposed method will recalculate each algorithm's special parameters (such as the k parameter for KNN) and recalculate the optimum values by following the same steps to obtain the best weights for each algorithm's self-improved algorithm ability. Otherwise, if the system structure stays stable, the calculated weights will be used to detect faults. In that case, structural changes means the training dataset must be changed, so the parameters of each algorithm must be recalculated, and PSO will optimize the weights again and again until ane accurate result is obtained.
7) If there is no structural change e.g., add/drop a new line, adding new renewable sources, step-6 would remain as indicated.

Since each algorithm has pros/cons for different characteristics of datasets, all of them are combined together to obtain the powerful sides of each.

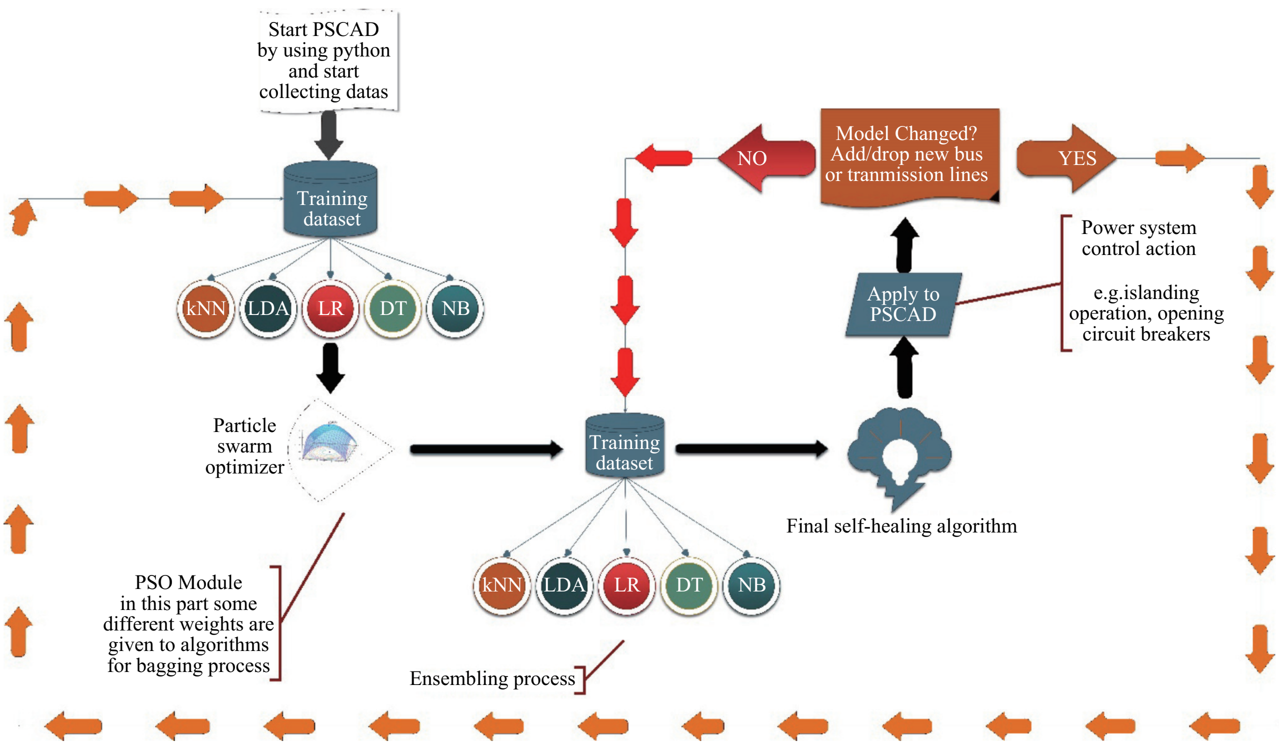

Fig. 3. Workflow for the PSO based weighted ensemble algorithm.

As a result, the proposed method becomes flexible and adaptive in case of any structural changes, which is a very normal and frequent behavior for the power system. This method does not require applying any signal processing techniques or any other pre-processing method, such as feature selection techniques, but at the same time, it can obtain very high accuracy even with raw data. Most of the methods use feature selection techniques to analyze the training data to obtain high accuracy results for the given dataset. However, the same selected features, or parameters that are used in the specific algorithm, can fail on another dataset, or scenario, because of their different characteristics. Thus, the proposed methods should be dynamically adapted to the collected data, which is rare and hard to optimize and apply in the real environment. It is noted that, with the proposed method, real-time processing could be possible since it has an ability to work with unprocessed newly collected data, as one of the powerful benefits with the self-healing adaptive background.

In the ensemble method, the key point is that the system will give 0 weight to the algorithm if it is not needed in the selected set. Each weight represents the power rate of the algorithm for the given data set during the soft-voting process. The PSO finds the best bag and provides the weights for each classifier in the combination. The generalized approach is shown as follows:

$$M=\{mla_1, mla_2, \ldots mla_{\mathrm{N}}\}, \quad \text{ML Algorithms} \tag{5a}$$

$$K=\{i_0, i_1, \ldots, i_k\}, \quad \text{Class Labels} \tag{5b}$$

$$W=\{w_1, w_2, \ldots, w_{\mathrm{N}}\}, \quad \text{Weights} \tag{5c}$$

$$\theta(M, W, K)=\arg\max_i \sum_{j=1}^{\mathrm{N}} w_j * p(mla_j|i) \tag{5d}$$

$$PSO(mla_1, \ldots, mla_{\mathrm{N}})=\{w_1, \ldots, w_{\mathrm{N}}\} \tag{5e}$$

where M is the set of weak machine learning algorithms represented by mla, K represents the class labels -which is "fault" or "not fault" in the scope of this paper-, W shows the weights of the algorithms. $\theta(M, W, K)$ is the function of the bagging process, and PSO calculates the optimal set of weights for $\theta(M, W, K)$ that obtains the highest accuracy. See Fig. 5 for random fault conditions.

The main purpose behind this idea is explained in Fig. 4 with a mock-up example. With the proposed method, each algorithm will close the gaps of other collaborative algorithms and try to obtain a total consensus if there is a fault or not. However, this consensus should also be as fast as possible because of the time limitations while working in a real-time environment. By using the best-scored classifier combinations and their calculated weights, the proposed model will be able to run the ensemble algorithm in real-time for islanding detection. Please note that the weight calculation process is computed just once unless there is no modification on the power system topology. In case of any structural changes in the power system model, the proposed algorithm will detect that difference and continuously train itself until it reaches saturation.

V. Results And Discussions

The islanding or fault situation must be detected as fast and as accurate as possible, and for this purpose, conventional signal processing techniques have aided in obtaining great predictions with machine learning algorithms. In addition to these techniques, many feature selection methods are applied in most of the techniques in literature to deal with deficiencies

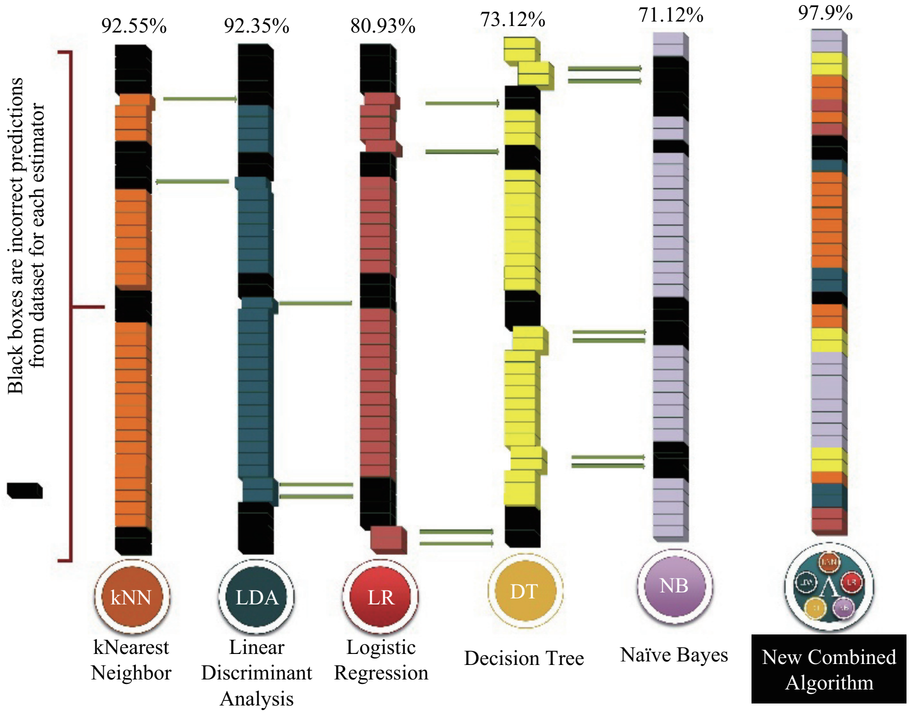

Fig. 4. PSO effects for each ML algorithm.

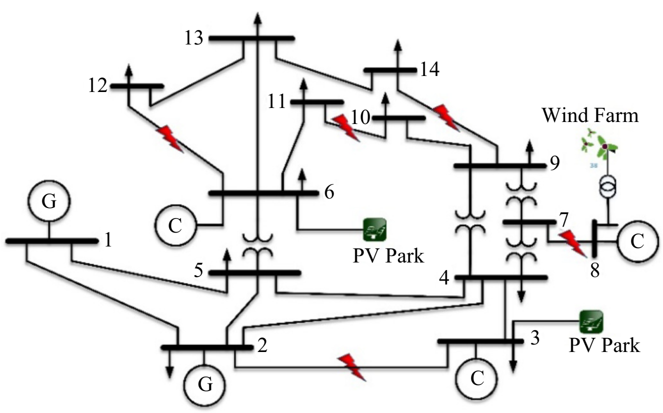

Fig. 5. Modified IEEE 14 Bus study system including renewable sources.

and system defects. However, they focus on the given dataset and provide excellent results for the specific state. When the technique provides high accuracy rates with feature selection, the same technique could fail on a different or dynamic data structure. When a ML algorithm is improved and specialized for a power system structure, it cannot be used on different structures or it can fail in cases where there is any differences in the power system structure. Thus, most of the common solutions are not applicable in the real environment. Many improved ML techniques show very high accuracy results, which means these improved models memorize the data instead of learning. Thus, it can be easily recognized, when the algorithm results in 100% accuracy, when there is an overfitting problem.

To overcome these situations, a weighted and self-healing ensemble technique has been proposed in this study by choosing 5 most robust machine learning algorithms; The IEEE 14 bus and IEEE 39 bus power system models are used to show the effectiveness of the proposed weighted ensemble-based machine learning approach for fault detection. The standard power system parameters are implemented during the PSCAD simulations running on an IEEE 14 bus model [35]. In addition to the well-known IEEE 14 bus model, the proposed method is also applied to the modified version, shown in Fig. 4, to compare the performances under entirely different characteristics of power systems in pointing out its adaptive and self-healing schemes. In this scenario, the IEEE 14 bus model system has been modified connecting renewable sources at buses 3, 6, and 8 by providing intermittency and uncertainties of voltage, phase angle and frequencies to test the proposed method's adaptivity. In all three cases, PSCAD/EMTDC software is coupled with Python to solve the problems and obtain solutions in a co-simulated platform to mimic real-time scenarios. PSCAD is being used to simulate the power system and Python for implementing ML algorithms. The time step of the co-simulation is kept as 50μs. By running the simulation 5 sec, 210.000 of voltage, frequency and phase angle data are generated for analysis as a CSV file format. About 80% of the gathered data is used for training the algorithm and then 20% of the remaining data is used for the testing of each algorithm.

Cross-validation was chosen as five, which means the algorithms test the next 20% part of the dataset and this process continues five times until all data was used for the test. Than the results are obtained by taking an average of five different accuracy results. For example, kNN accuracy results are 89%, 93.25%, 97%, 91%, and 92.5% for each cross-validation cycle. The average of the five accuracy values is 92.55% as stated in Table III. The overfitting problem was handled in this way and ensures more realistic results.

After these steps, each ML algorithm (kNN, LDA, LR, NB, DT), boosting algorithm (AB, GB), and finally proposed PSO based ensemble method are investigated and compared in terms of effectiveness, adaptivity, and process-time under two different case scenarios.

A. Case 1: Fault Analysis and Comparison

In power system applications, symmetrical and unsymmetrical faults are occurring. In that perspective, we choose one of the most common occurring faults, which is an unsymmetrical fault. In this study, unsymmetrical faults are applied. In practice, just 2%–5% of symmetrical faults are occurring in the power system. This unsymmetrical fault type is one of the most difficult ones to detect, compared to severe double-line-to-ground (2LG) and three-line-to-ground (3LG) faults. The system performance has really been tested in the most challenging situations: single-line-to-ground (1LG) faults.

In this study, the 1LG fault has been selected and applied randomly for 0.15 s in lines (7–8, 10–11, 9–14, 2–3, 6–12) at 5 different time instants (1.6, 2.3, 2.8, 3.8, 4.4), respectively. Different fault locations are chosen to observe the effect of the proposed algorithm as the voltage drops vary randomly. For instance, the voltage response at bus 9 is given in Fig. 6 to show the fault's effect on the voltage response. Also, for each bus, the frequency and phase values have been used for the prediction process. The PSCAD timed fault logic box creates faults, and the impedance is selected as 100 kΩ for the default. Fault locations are respectively;

- Line 7–8, 63 km, close to bus 7,
- Line 10–11, 23 km, close to bus 11
- Line 9–14, 43 km, close to bus 14
- Line 2–3, 35 km, close to bus 3
- Line 6–12, 35 km, close to bus 12

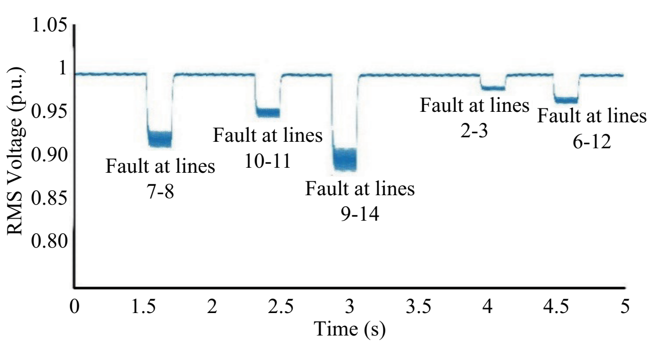

Fig. 6. Voltage response at bus 9 (1 LG fault).

Table II shows how the PSO-based weighted ensemble method, which is a combination of multiple (at least 2, up to 5) ML algorithms, can work on-fly effectively compared to well-known boosting algorithms for an IEEE 14 bus standard model.

Table II also shows a comparison of the proposed PSO-based ensemble method with other boosting algorithms (GB and AB), in terms of time and accuracy viewpoints using the IEEE 14 bus model. Accuracy results show the proposed algorithm is around 5% more accurate, and also much faster

TABLE II
DECISION PARAMETERS AND COMPARISON OF ACCURACIES FOR EACH CLASSIFIER ON CLASSICAL IEEE 14 BUS MODEL

Algorithm	Parameters	Algorithms Individual Process Times (s)	Accuracy Results %
K Nearest Neighbor	Neighbor = 9	1.7	92.55
Linear Discriminant Analysis	Tolerance = 0.0001 Solver = svd	1.49	92.35
Logistic Regression	–	2.3	80.93
Naïve Bayes	–	0.6	73.12
Decision Tree	criterion = gini splitter = best	2.0	71.12
AdaBoost	–	0.57	93.13
Gradient Boosting	–	0.29	92.85
XgBoost [36]	–	0.11	97.62
PSO-Ensemble	Combination of 5 ML PSO Weights kNN 0.51 LDA 0.49 LR 0.24 DT 0.14 NB 0.82	0.021	97.93

then individual and boosting algorithms. The proposed method is also achieving slightly better accuracy results, compared to the XgBoost algorithm [36].

Process time-wise, the PSO-based Ensemble algorithm works faster than other approaches because of its bagging scheme and pre-computed background in which, as an evolutionary algorithm, PSO particles communicate with each other and they use their own previous best solution. Thus, it can reach final results very quickly. Each of the ML algorithms are strengthened by PSO, so PSO trains the algorithms to find the best weights, however, this process only happens one time unless the power system structures are kept constant. The same collected dataset used for comparison with boosting algorithms and the proposed method gives better results in terms of both process time and accuracy. The bagging application is faster than any other boosting algorithms (AB and GB) due to the parallel processing structure. In the proposed method, different powerful ML algorithms close their gaps as they work together. That is the reason why the proposed method gives better results.

B. Case 2: Power System Structure Adaptivity Test

In this case, two different rigid (IEEE-39 bus and IEEE-14 bus modified) models are tested. The structural change is reflected in the simulation by adding 3 renewable sources at buses 3, 6, 8 and this system is named as a modified IEEE 14 Bus model to test the proposed method in adaptivity and self-healing. The 1LG fault is also considered in this case. Because one of the most difficult detections is a 1LG fault, its captured dataset of the voltage, frequency and phase angle signals are considered for further analysis. For the IEEE-39 bus system, faults are applied randomly to locations for 0.15 s in lines (1-39, 3–4, 6–11, 9–39, 13–14, 16–19, 19–33, 23–24) at 8 different time instants (1.2, 2.4, 3.4, 4.4, 5.4, 6.4, 7.4), respectively.

The nature of PSO adopts structural changes immediately and efficiently. The proposed method detects the structural changes, and if they happen, the best-tuned parameters of each algorithm are re-calculated again. Then, PSO gives different weights to each of them again. Because structural changes affect the dataset, previous parameters and weights may not be useful in that case. An additional explanation can be seen in Fig. 3, step 6.

After showing the success of the proposed method, each well-known algorithm and boosting algorithm results are obtained and tested to be compared with the proposed method using the modified IEEE 14 bus model. In this case, accuracy results can be seen in Table III which shows that the proposed method adaptivity is very high when compared with other methods. Also, the IEEE 39 bus model has been tested under the same conditions and the results are shown in Table IV.

TABLE III
DECISION PARAMETERS AND COMPARISON OF ACCURACIES FOR EACH CLASSIFIER ON THE MODIFIED IEEE 14 BUS MODEL (WITH PV)

Algorithm	Parameters	Algorithms Individual Process Times (s)	Accuracy Results %
K Nearest Neighbor	Neighbor = 9	1.94	92.61
Linear Discriminant Analysis	Tolerance = 0.0001 Solver = svd	1.63	87.38
Logistic Regression	–	2.45	76.3
Naïve Bayes	–	0.83	84.5
Decision Tree	criterion = gini splitter = best	2.13	82.38
AdaBoost	–	0.57	81.23
Gradient Boosting	–	0.29	91.35
XgBoost [36]		0.11	93.48
PSO-Ensemble	Combination of 5 ML PSO Weights kNN 0.69 LDA 0.40 LR 0.39 DT 0.23 NB 0.85	0.036	96.68

TABLE IV
DECISION PARAMETERS AND COMPARISON OF ACCURACIES FOR EACH CLASSIFIER ON THE IEEE 39 BUS MODEL

Algorithm	Parameters	Algorithms Individual Process Times (s)	Accuracy Results %
K Nearest Neighbor	Neighbor = 9	2.23	79.59
Linear Discriminant Analysis	Tolerance = 0.0001 Solver = svd	1.93	78.14
Logistic Regression	–	2.97	87.02
Naïve Bayes	–	1.23	81.20
Decision Tree	criterion = gini splitter = best	2.83	91.00
AdaBoost	–	0.59	73.17
Gradient Boosting	–	0.89	94.15
XgBoost [36]		1.37	95.89
PSO-Ensemble	Combination of 5 ML PSO Weights kNN 0.305 LDA 0.226 LR 0.065 DT 0.139 NB 0.772	1.13	96.61

- There are no signal processing techniques and they don't require threshold tunning. In this study, only a raw dataset has been used for training and prediction parts. As a result of this method, any waste of time is avoided. Also, it is not necessary to have too much computational power. Because ML algorithm's parameters and PSO optimizations processes are just one time applied until power system structure changes occur. If the power system structure changes, the proposed method calculates new parameters and weights for each algorithm.
- Most of the popular algorithms (5 of them) are combined adaptively, and that mechanism obtains a real-time self-healing feature. The proposed method automatically calculates the weights of each algorithm. When a faulty condition happens, or the current weights cannot give sufficient results in a timly manner, the training part restarts to overcome this issue, see Fig 3.
- Boosting algorithms are applied for prediction, and so final accuracy results show that the proposed method works successfully and can obtain the highest accuracy which is more than the boosting algorithms, such as AdaBoost and gradient boosting.
- The proposed Method can update by itself, in case of any existing topological differences.
- As an optimization algorithm, PSO, optimizes popular algorithm's weights to achieve an as accurate result as possible.
- IEEE allows 2 second delays [37], but in this case, the experimental prediction time interval is 0.001. So the proposal method achieved almost 2,000 times faster detection than IEEE's allowed time delay. Also, for the different random faults, the algorithm continues to show the same success.
- Any possible voltage fluctuation or bus system violence can mislead final results, therefore threshold setting is not a good solution so we don't use any threshold settings for our proposed method.
- Tables III and IV also show that the proposed method provides almost 5% better accuracy performance compared to boosting algorithms and individual ML algorithms accuracy results in both modified IEEE 14 bus models.
- In the standard topology, XgBoost and the proposed method seem very close to each other in terms of accuracy performance. However, when the topology is changed, and the system fluctuates more, the results show that the proposed method is clearly overperforming XgBoost.

The results given in Table III and Table IV show that some ML algorithms, such as kNN or GB in Table III, can provide high accuracy results in some cases, however, they may not be able to reach the same levels on different structures as in

Table IV. That is the main reason to develop the bagging based ensemble algorithms to strength deficiencies and weaknesses in the ML algorithm in different scenarios and/or structures.

It is noted that Gradient boosting works more accurately than Adaboost on the modified IEEE model. The main reason for this is by adding renewable sources, the gathered data has more noise because of voltage/frequency fluctuations, and therefore, the Adaboost algorithm can be easily defeated by noise when compared with the Gradient Boosting. With respect to accuracy and process time, the proposed PSO based Ensemble method shows very high results over boosting algorithms. Also, the proposed method, compared with the XgBoost algorithm, clearly outperforms. The results are promising for both conditions.

All these comparisons show that the proposed method has an adaptive characteristic and it can work significantly better than any platform without changing pre-computational techniques so that it provides a specific solution for a given data set. Since the PSO weights are calculated dynamically, whenever needed, the PSO-based Ensemble method can be easily adapted in different schemes and power topologies, so that it can train and predict data at the same time.

The performance of the PSO-based Ensemble method is not significantly affected in uncertain cases in voltage and frequencies, such as adding renewable sources. This means that the addition of renewable sources affects the individual machine learning algorithms' performance, however, the proposed method's progress is extremely good, even in this situation.

VI. Conclusion

The PSO-based Ensemble method is proposed in this study to detect faults in the power system. The proposed algorithm is tested on different models, such as IEEE 14, IEEE-39 bus systems and modified model by adding newly commissioned renewable sources, as a means to present the case of structural change of the power system.

In the proposed method, there are no signal processing or feature selection techniques needed, and just raw dataset (input signal voltage, frequency and pahse angle) is used for the predictions. Thus, the proposed method is not just specialized for the dataset. According to the results, it is also adaptive and flexible for any type of structure-based dataset. It is found that the proposed method provides much greater accurate results than individual machine learning algorithms using three IEEE models (14 bus-39-bus and PV added). The proposed method's accuracy rates are calcualted as 97.93% for the IEEE classical model and 96.68% for the modified (PV added) model and 96.61% for the IEEE-39 bus model. While IEEE 1547 standards allow 2 second delays to detect any possible faults, the proposed method obtains better results, up to 0.021 s for the IEEE 14 bus and 0.036 s for the modified IEEE 14 bus model. This means, the computational time is almost 1% of IEEE standards which is small enough for a power system study. Thus, the proposed method will provide higher and faster results than the most popular machine learning algorithms and also provides adaptivity for any structural changes.

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Levent Yavuz graduated from the Erciyes University Physics and Electrical Electronic Engineering and currently studying as Research Assistant at the Abdullah Gül University.

He established a company, MaM High Tech Corp, by Tubitak Foundation as an entrepreneur.

He received 5 patents. His research interests include machine learning, deep reinforcement learning, virtual power plant, microgrids, solar generation forecasting, nuclear energy and renewable energy systems.

Ahmet Soran received the B.Sc. and M.Sc. degrees in Computer Engineering from TOBB ETÜ, Ankara, Turkey, in 2009 and 2012, respectively, and the Ph.D. degree in Computer Science and Engineering from the University of Nevada, Reno (UNR), in 2017. He joined the Computer Engineering Department, Abdul- lah Gül University, Kayseri, Turkey, in 2018. His research interests include graph theory applications, network communications, device-to-device protocols, network and traffic management, network architecture, smart grids, the Internet of Things, cyber security, and privacy.

Ahmet Önen received the B.Sc. degree in Electrical-Electronics Engineering from Gaziantep University, in 2005, the M.S. degree in Electrical and Computer Engineering from Clemson University, in 2010, and the Ph.D. degree from the Department of Electrical and Computer Engineering, Virginia Tech, in 2014. He is currently working as an Associate Professor with Sultan Qaboos University. His research interest includes the development and deployment of renewable energy along with AI.

Xiangjun Li (M'06–SM'12) received the B.E. degree in Electrical Engineering from Shenyang University of Technology, China, in July 2001, and his M.E. and Ph.D. degrees in Electrical and Electronic Engineering from Kitami Institute of Technology (KIT), Japan, in March 2004 and March 2006, respectively. From May 2006 to March 2010, he worked as a postdoctoral research fellow at the Korea Institute of Energy Research (KIER), Daejeon, Korea, and Tsinghua University, Beijing, China, respectively. In March 2010, he joined the Energy Storage and Electro-technics Department (ESED) (before: Electrical Engineering and New Material Department), China Electric Power Research Institute (CEPRI), Beijing, China, where he has been engaged in the topic of integration/control/SCADA/application technologies for large-scale multi-type battery energy storage systems/stations, distributed generation systems, electric vehicles, and micro-grids. He is the director of energy storage system integration & configuration technology laboratory for the ESED of CEPRI from June 2019. He is the director of large-scale energy storage technology and application laboratory of CEPRI from May 2020. His research interests include renewable energy power generation, electric energy saving/storage technology, and power system engineering. He has served as the Chair of the IEEE CIS Task Force on ADP and RL in Power and Energy Internets. He has also served as the editor of the IEEE Transactions on Sustainable Energy, editor of IET Renewable Power Generation, editor of Protection and Control of Modern Power Systems (Springer journal), and guest editor of Engineering (Elsevier journal). He has been awarded three U.S. Patents of Invention and 79 Chinese Patents of Invention. Prof. Li is a Fellow of IET, chartered engineer, and is one of the senior members of IEEE, CSEE, CAS, and CES, etc.

S. M. Muyeen (S'03–M'08–SM'12) received his B.Sc. Eng. Degree from Rajshahi University of Engineering and Technology (RUET), Bangladesh formerly known as Rajshahi Institute of Technology, in 2000 and M.Eng. and Ph.D. Degrees from Kitami Institute of Technology, Japan, in 2005 and 2008, respectively, all in Electrical and Electronic Engineering. At the present, he is working as a full Professor in the Electrical Engineering Department of Qatar University. His research interests are power system stability and control, electrical machine, FACTS, energy storage system (ESS), Renewable Energy, and HVDC system. He has been a Keynote Speaker and an Invited Speaker at many international conferences, workshops, and universities. He has published more than 250+ articles in different journals and international conferences. He has published seven books as an author or editor. He is serving as Editor/Associate Editor for many prestigious Journals from IEEE, IET, and other publishers including IEEE Transactions on Energy Conversion, IEEE Power Engineering Letters, IET Renewable Power Generation and IET Generation, Transmission & Distribution, etc. Dr. Muyeen is the senior member of IEEE and Fellow of Engineers Australia.