International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 07 Issue: 05 | May 2020 www.irjet.net p-ISSN: 2395-0072

Machine Learning and Game Theory in Microgrids: A Survey of Applications, Benefits, Current Trends and Future Research

Sharif Atique[1], Stephen Bayne[1]

[1]*Department of Electrical and Computer Engineering, Texas Tech University, Lubbock, TX 79409, USA*

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Abstract - *Microgrids have gained popularity as an efficient means of integrating distributed energy resources; a case bolstered by the modularity and autonomous operation. However, a microgrid is still a relatively new area in the research domain and there are numerous issues to be addressed for their wide scale integration into the existing power systems. This review paper discusses the recent trends and applications of two fascinating areas of research, machine learning and game theory, in dealing with finding autonomous solutions to microgrids. Broadly, the applications of machine learning in microgrid research have been studied based on few of the key aspects microgrid: detection, system design and prediction. Moreover, game-theoretic applications in microgrids have been summarized. The research area of microgrid being relatively untapped, machine learning can play a significant role in streamlining the operation of microgrid towards building the self-sustaining smart grid system.*

***Key Words*: Machine learning, game theory, microgrid, event detection, prediction, system design**

1. INTRODUCTION

In a simplistic view, machine learning is about doing a predictive analysis with available data using the smartest possible learning algorithms. Although there is already a host of machine learning algorithms, and it is being continually improved upon. The three fundamental building blocks for any machine learning algorithm can be identified as representation, evaluation, and optimization [1]. The representation offers the core logical structure of the algorithm that is designed to validly process the input to predict the output in the form of classification or regression. The evaluation functions or objective functions score the representations to distinguish the good classifiers from the bad ones; and based on the model, the evaluation functions may be internally used by the algorithm and can be different from the external evaluation that is set to obtain the output layer decision. Lastly, the optimizer gets the learning algorithm to efficiently converge to its highest-scoring classifier or predictor. The overall idea of machine learning well captured in Table 1 [1] for a guiding reference throughout this paper. Although the list is not exhaustive, as we explore machine learning applications in microgrid research, we shall mostly refer to the machine learning algorithms by their representation identities skipping the details of the internal evaluation and optimization techniques under the hood of the machine learning models. It is ought to be mentioned that whereas the table represents the algorithms by their independent identities, in a modern system-based approach, often several of those algorithms are combined to form ensemble models which significantly enhances the performance. The idea of applying machine learning for power grids is in focus for some time now. Machine learning had been proposed for the New York City power grid a few years back [2]. In this work, current trends and applications of machine learning have been studied for microgrid, which is a fundamental component of future smart grids. As we explore the body of knowledge, we shall see that microgrid research employs the machine learning techniques ranging from simplest of representations like linear regression or naïve Bayes to far more complex ensemble models consisting of multiple neural networks.

Table-1: Components of machine learning algorithms

Representation	**Evaluation**	**Optimization**
Instance-based K-nearest neighbor Support vector machines **Hyperplanes** Naive Bayes Logistic regression **Decision trees** **Set of rules** Propositional rules Logic programs **Neural networks** **Graphical models** Bayesian networks Conditional random fields	Accuracy/Error rate Precision and recall Squared error Likelihood Posterior probability Information gain K-L divergence Cost/utility Margin	**Combinational optimization** Greedy search Beam search Branch-and-bound **Continuous optimization** **Unconstrained** Gradient descent Conjugate gradient Quasi-newton methods **Constrained** Linear programming Quadratic programming

Based on the type of applications, the machine learning applications can be broadly divided into three categories: event detection, system design and prediction. These three areas of application are detailed in section 2, 3 and 4, respectively. Game-theoretic applications for microgrid are discussed in section 5. Finally, the conclusion and possible future researches are explained in section 6.

2. EVENT DETECTION

Microgrid is seen to be the obvious route for integration of distributed generation (DG). However, the integrated microgrid into the existing power grid infrastructure is occasionally prone to islanding. Islanding occurs when some portion of microgrid is active despite not being connected to the main grid. Islanding happens because microgrid continues to be connected to the DGs. According to [3], detection of islanding and subsequent separation of the distributed generators should be completed within 2 seconds to maintain power quality and ensure safety. In [4], performances of five machine learning techniques have been compared using the Waikato Environment for Knowledge Analysis (WEKA) toolbox for timely detection of islanding. Four different features are measured at the point of common coupling (PCC) to detect events and they are: (a) voltage, (b) frequency, (c) rate of change of voltage, and (d) rate of change of frequency. This work is based on the IEEE 13 bus system depicted in fig.1.

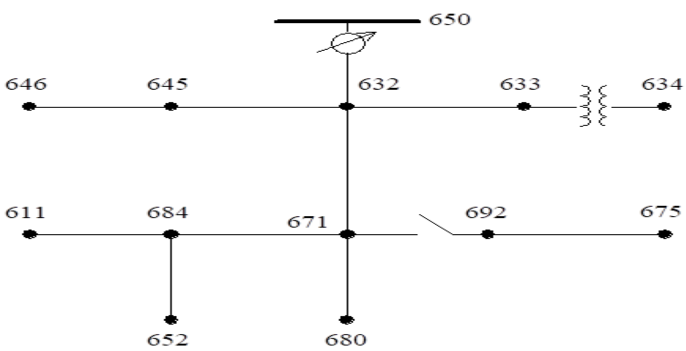

Fig-1: IEEE 13 bus system

The five algorithms that have been compared are: (1) Nearest Neighbor (NN), (2) Bagging Classifier (BC), (3) Lazy-K, (4) Naïve Bayesian (NB), and (5) Random Forest. Three types of generation scenarios were analyzed: (a) inverter-based solar generation (IDG), (b) synchronous generator-based generation (SDG), and (c) a combination of both (CDG). A ten-fold cross validation process was utilized to assess the results. Among all the classifiers, RF performed best in terms of accuracy, with lazy-K being the worst, across all three generation scenarios in general. The performance of the classifiers degrades if one time train test split is used instead of the above mentioned cross validation. In terms of features used, the classifiers work better when all the features are used. The absence of the rate of changes features significantly reduces the accuracy of the classifiers. In terms of detection time, random forest fares better than the other classifiers to attain a certain accuracy, with lazy-K again providing the least satisfactory result. The results have been summarized in table 2 [4].

Table-2: Performance summary from [4]

	Classifier	IDG	SDG	CDG
10-fold cross validation	N.N	98%	99%	94%
	R. Forest	99%	96%	100%
	Bagging	99%	93%	99%
	Lazy K*	81%	71%	84%
	Naive Bayes	99%	97%	86%
Split data segments	N.N	92%	90%	88%
	R. Forest	88%	90%	96%
	Bagging	64%	86%	96%
	Lazy K*	64%	54%	66%
	Naive Bayes	64%	96%	84%
Voltage	N.N	81%	81%	83%
	R. Forest	81%	81%	88%
	Bagging	80%	81%	87%
	Lazy K*	81%	83%	87%
	Naive Bayes	77%	80%	82%
Frequency	N.N	87%	82%	83%
	R. Forest	87%	83%	85%
	Bagging	81%	81%	85%
	Lazy K*	87%	71%	77%
	Naive Bayes	77%	76%	77%
Voltage and Frequency	N.N	75%	92%	85%
	R. Forest	75%	92%	87%
	Bagging	78%	81%	83%
	Lazy K*	75%	92%	83%
	Naive Bayes	80%	77%	76%

Article [5], as its background, voices a case for local hybrid techniques that combine passive techniques and artificial intelligence for islanding detection. Whereas they eliminate the need for the communication expenses and complexities associated with active methods; they offer significant efficiency in terms of early detection and accuracy over passive-only methods. In different methods proposed in the literature, the feature extraction was done through discrete wavelet transform (DWT), Parsevals theorem and other data mining approaches which then were fed to different classification models ranging from probabilistic neural network (PNN) to classification and regression tree (CART). In most cases, the goal is to obtain an optimal threshold setting for the passive islanding detection by the two-step process of extracting appropriate features and then applying the extracted features into the machine learning models. The good performance of intelligent methods combining DWT and decision tree [6]; and in another case, the combination of estimation of signal parameters via rotational invariance technique (ESPRIT) with a Naïve Bayes classifier [7] inspired another method combining phase-space technique with PNN as classifier [8, 9]. This also emphasizes the promise of emerging extreme learning machine (ELM) technique that was successfully deployed for real time assessment of system stability [10, 11] and goes on to explore the ELM technique for microgrid islanding. As the work uses phase-space model for feature extraction, it refers to the methods with which phase-space can be reconstructed from a time series through embedding theorem [8, 9]. The embedded signal is extracted from Euclidian norm of phase A, B and C. The embedded signal information is then used as the voltage trajectory. The paper then goes onto describe the ELM with the single hidden later architecture and 3-step learning process. Which it argues to favor ELM as a classification technique over back-propagation artificial neural network, support vector machine (SVM) and DT [10-12], it points to the inconsistency and lack of robustness of the technique due to randomly selected input weights. That weakness, however, is overcome in this work with tailored ELM ensemble classifier [10, 11]. In the ensemble scheme, the single learners tend to compensate each other and improve the overall accuracy. The ELM based adaptive classifier is then represented as following pipeline with each task described in terms of their sequential sub-steps: Model Structure → Learning Process → Classification Process → Parameter Optimization → Adaptive Decision-Making Mechanism. While these steps reflect the standard machine learning sequence, the parameter optimization techniques involving evolutionary computation (EC) approach as genetic algorithm (GA), particle swarm optimization (PSO) or differential evolution (DE) deserves distinct mention. For the adaptive decision making mechanism, the events of islanding and non-islanding are classified by a series of ensemble ELM classifiers with different decision speed. For evolutionary computing (EC), if decision cycle T cannot give a credible classification, it will continue up to next decision cycle T+1, thus offering adaptive decision and increased accuracy with increased number of cycles. Unlike the conventional classifier, the proposed adaptive classifier evolves with more incoming data; which leads to statistical performance indices like accumulative accuracy, average decision speed, and average islanding detection accuracy [11]. As the system setup, this experiment simulated two identical synchronous DG as well as power-electronics interfaced DG to showcase that the methods can universally work for all DG settings. The test results showed that for all the test systems, the method performed with better accuracy in comparison to random forest.

Re-emphasizing the importance of islanding detection for microgrids with distributed generation from power quality and safety perspective, [13] approaches the issue from a well-drafted background. Besides listing the passive and active techniques of islanding detection prevailing in research and literature, it draws a high level comparison between the passive and active techniques primarily in the light of non-detection zone (NDZ). While arguing that the passive methods, which are based on pre-setting the threshold values of parameters like voltage and frequency, operate at a large NDZ resulting in misidentified islanding or premature cut-off from the grid. The article proposes a machine learning based islanding detection technique which offers an artificial neural network (ANN) as the classifier where the features for the neural network model is extracted from the rate of change of frequency (ROCOF) measurement in consecutive cycles of transient state signal. The machine learning model is applied to 80kW DG setup simulated in Simulink with PQ control implemented through necessary Phase-Locked-Loop (PLL) and dq-abc transformations. Complying with the basics of supervised machine learning, the ANN is trained with real examples of islanding and non-islanding scenarios with respect to statistical features that are obtained from the differential transient ROCOF signal in two consecutive cycles. The non-islanding event examples include one, two or three phase faults, connection or disconnection of the motor loads, capacitor banks, unbalanced and non-linear load. Upon training and testing, the best ANN model was then used for real time islanding detection. For the evaluation of ANN structure, multi-layer perception (MLP) and radial basis function (RBF) were both tried and compared to achieve the least mean squared error (MSE). One of the key takeaways for this experiment was that an MLP structure of three neurons in the hidden layer yielded 99.9% accuracy in classification. On the other hand, RBF structure needed 150 neurons in the hidden layer to attain the same level of accuracy. The simulation results convincingly illustrated that the proposed technique minimizes the NDZ as compared to passive techniques. The real time islanding detection is also expected to enable dynamic changes in inverter control structure as an inverter has slightly different role in a grid-connected scenario as opposed to an islanded scenario.

As we discuss the detection issues related to the microgrid, fault detection is as important as the islanding event detection. A microgrid can be more resilient and automated if self-healing capability can be incorporated. A microgrid with self-healing capability can perform fault detection, fault clearing and restoration on its own. A distributed machine learning based fault detection method in a self-healing microgrid is proposed in [14]. The proposed method is distributed as the decisions are made at the device level and no centralized control is applied. So, the distributed approach is cost effective and faster than centralized approaches. The system that has been used for analysis in this work contains both dispatchable and non-dispatchable generators. Dispatchable generation include synchronous generator based hydro and diesel generators. On the other hand, non-dispatchable generation include solar and wind power. Series compensators with two modes of operations are used near the generators. When a fault occurs in an area, the series compensator in that area would operate in bypass mode instead of blocking mode. Four attributes and three features for each of the attributes were used for training purpose. The attributes are: (a) rotor speed, (b) deviation of rotor angle, (c) generated reactive power, and (d) terminal voltage. The first two features are based on the sharpness and width of the local maxima and the final feature is the frequencies available from the time series data. Finally, three factors are derived, with each factor corresponding to a specific feature. The factors are defined as prominence, width and frequency factor. A few events are simulated for the training purpose and each event has distinct values for all three features. Finally, a bootstrap aggregation classifier was used to train. A bootstrapping classifier divides the training dataset into several smaller base classifiers and the final decision is made by aggregating the decision of all the base classifiers. As this technique can also correct previous errors, this can be termed as a bagging and boosting technique. As compared to other machine learning algorithms like ANN, CART and K-nearest neighbors (KNN), this proposed algorithm shows significant increase in accurately detecting an event.

An approach which combines machine learning algorithms along with signal processing techniques is proposed in [15]to develop a microgrid protection scheme (MPS) that would detect and classify a significant range of faults in a microgrid. This work considers a microgrid with distributed generation based on both synchronous generator and inverter. Both the grid-connected and islanded microgrid with radial and mesh structure have been studied in this work. Currents in all three phases at the target are the initial inputs. Initial mode functions (IMFs) are generated by applying empirical mode decomposition to these current signals. Afterwards, the features needed for the machine learning techniques are derived by using Hilbert-Huang transformation to the IMFs. Finally, these features are used as inputs for the machine learning methods to detect and classify the faults. In the machine learning portion, 70% of the total data are used for training purpose. In this work, the following three machine learning algorithms are utilized for testing and comparison purposes: Naïve Bayesian classifier (NBC), extreme learning machine (ELM), and support vector machine (SVM). All the machine learning techniques demonstrate significantly better detection performance than conventional overcurrent and differential relays. Among the machine learning techniques, the best accuracy is obtained while using ELM, with NBC coming in second. Irrespective of the machine learning method, the overall accuracy is more than 96%.

Power transformers are integral parts of a power grid and any fault associated to the transformers can lead to power outage and huge economic loss. So, accurate prediction of impending faults in the transformers is of utmost importance. Traditionally the dissolved gas analysis (DGA) is used to diagnose the working state of a transformer and detect potential faults. DGA is quite effective for common faults. However, the effectiveness decreases for subtle faults as it does not consider additional parameters like oil temperature and load current, outside the states of certain gases. In [16], the authors have developed a novel scheme, termed PCA_IR, to detect potential faults in transformers by combining three techniques. These techniques are: Pearson correlation coefficient (PCC) to find additional relevant parameter correlated to the dissolved gases, principal component analysis (PCA) to reduce the dimensionality of the dataset, and finally back propagation neural network (BPNN) to classify faults. The first part of this work attempts to find out correlation between dissolved gases and other parameters by calculating the PCC. In this paper, oil temperature is found to have a PCC of 0.81 with the sum of concentrations of all hydrocarbon gases. Therefore, oil temperature is considered as the eighth feature besides the seven dissolved gases. As new features are added, the accuracy increases but the computational speed decreases because of an increase in the dimension of the dataset. The second part of this work takes care of computational speed issue by reducing the dimensionality using PCA. Finally, the principal components are fed into the BPNN to classify the faults. The results demonstrate that the accuracy of classification goes from 61.30% to 91.57% with the addition of additional feature and application of PCA. Moreover, PCA_IR is faster than regular BPNN when the number of features is greater than 6. Even with smaller number of features (<6), PCA_IR is better suited to handle larger data sets because of its scalability.

3. SYSTEM DESIGN

Ensuring power quality (PQ) is of utmost importance for maintaining the reliability of the grid. Power quality also plays an important role in extending the lifetime of equipment and saving energy costs. Power quality in a grid can be monitored by installing PQ meters. However, PQ meters are expensive which makes the choice of optimum number of PQ meters in a grid an interesting challenge. [17], using a machine learning approach, addresses this issue. Placement problem with phasor measurement units has been analyzed in [18]. The first part of this work models the latent features of a device; in other words, behavior of the equipment in the grid; using historical data and then uses k-fold cross-validation technique to test the accuracy of these features. In the next part, the microgrid is designed as a data network where the equipment, power links and flow of power are analogous to nodes, data links and data flow, respectively. The final part of the work deals with the application of a machine learning algorithm for the optimal placement of PQ meters. The core idea is to install a PQ meter in the segment where PQ is the most unpredictable. Two separate approaches have been proposed and compared in this work. The first approach is based on a Bayesian-network approach and applies the belief propagation (BP) algorithm to place the meter in the most unpredictable network segments. The second method is based on conditional entropy and it tries to place meters in such a way that would reduce the overall entropy of the system. This second approach is called MinEntropy method. Both the methods are evaluated for networks with different topologies (Both homogeneous and heterogeneous line and tree topologies, and IEEE 13 node test feeder) in terms of mean error rate and execution. Both the methods are quite efficient in minimizing error. However, the MinEntropy is significantly faster in its execution than the BP algorithm. Finally, both the methods are tested for cost effectiveness against a random method where the meters are placed randomly. Both the proposed methods require a smaller number of PQ meters to achieve a mean error rate of 5%.

Battery or energy storage is another important component of microgrid system design, especially since microgrids are extremely lucrative solutions for places with low penetration of electricity and off-grid locations. However, batteries are vulnerable and normally the first components to fail. That is why it is very important to keep track of the state of charge (SoC) and state of health (SoH) of batteries. The traditional method, which considers the chemical processes inside the battery, is complex and time consuming. Estimating the condition of a lithium ion battery has been tackled using machine learning method in [19]. In this work, the authors have proposed a regression technique based on extreme learning machine (ELM) in estimating the condition of a Li-ion battery and the results are very encouraging. The minimum RMS error is found to be 3.1% and 2.4% for SOC and SOH estimation, respectively.

Despite energy storage systems' importance in microgrid, the cost effectiveness of a microgrid without energy storage systems makes it an exciting proposition. However, the control scheme of such a microgrid is quite challenging. There would be situations, where primary control scheme like droop control mechanism cannot maintain a stable voltage when the load changes suddenly. This is a significant issue for microgrid as loads are relatively more volatile than a utility grid. Under these circumstances, microgrids need provisions for secondary voltage control scheme which would work in case the primary scheme fails. The authors have developed a decentralized secondary control scheme in [20], using machine learning techniques. The system model that has been used here (fig 2) as microgrid has both synchronous generators based thermal generation and renewable generation [21]. The secondary control scheme is applied at the synchronous generators and the renewable energy sources act as data sources to initiate the operation of the control scheme. The secondary control will always act after the primary scheme fails to stabilize the voltage. Using fifty test cases, an unsupervised K-means cluster is prepared, and five categories are defined for the clusters. After that, a classifier is established using bagged decision trees. The classifier is binary as it would only decide whether an event makes the system stable or unstable whenever it processes a new set of data. Finally, if the classifier invokes instability, a suitable neural network would be chosen which would predict the required rotor speed and field voltage of the synchronous generator for stable operation of the microgrid. Finally, the primary controller would change its course of action based on the neural network's predicted values. The simulations demonstrate the effectiveness of the proposed method, as the microgrid would become unstable without the secondary control mechanism. However, the results differ from cluster to cluster because of the frequency of clusters in the fifty test cases. Moreover, the overall accuracy of the proposed method can be enhanced if the training can be done with more test events.

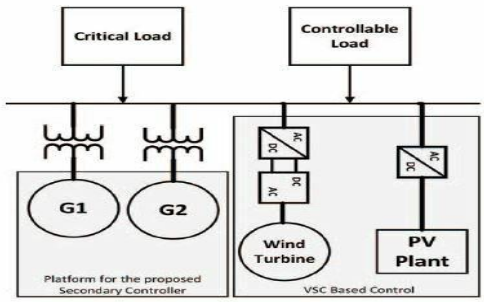

Fig- 2: Modified microgrid system model [21]

Demand-supply management is a key design aspect for any power system. As previously discussed, the supply side of a microgrid is inherently uncertain because of the intermittent nature of distributed renewable energy resources. Moreover, the demand side of a microgrid has more uncertainties than a regular grid because of the small scale of the operation and the weaker smoothing effect that results from it. Furthermore, the distribution of both the uncertainties can be different and non-Gaussian. The uncertainties of the loads follow a Gaussian distribution. On the other hand, the uncertainties associated with wind energy generation follow a non-Gaussian distribution [22-24]. An AC Microgrid model and its uncertainties are demonstrated in fig.3 and fig.4, respectively. The scheduling problem under all these circumstances have been tried to solve in [25], using a stochastic model predictive control (SMPC) method. First, the Gaussian distribution of the microgrid load uncertainty is modeled and forecasted using Gaussian process (GP) regression. Afterwards, the uncertainties related to wind energy conversion system (WECS) is modeled using SOWGP, which is an online probabilistic forecasting model for non-Gaussian distributions. The joint distribution of these uncertainties follows a non-Gaussian pattern. This work utilizes support vector regression (SVR) to derive the joint statistics, which in turn transform the original stochastic optimizing problem into a deterministic one and can thus be solved using traditional algorithms. This proposed method demonstrates its ability to do a better job of tracking the predefined trajectory for power exchange between microgrid and main grid, as compared to some traditional techniques. This proposed method also displays faster computation speed as it avoids the use of time-consuming Markov chain Monte Carlo (MCMC) sampling.

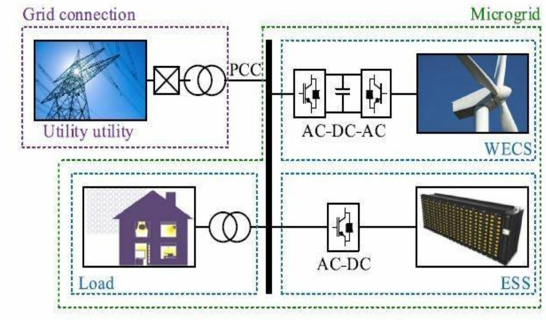

Fig-3: AC microgrid system model used in [25]

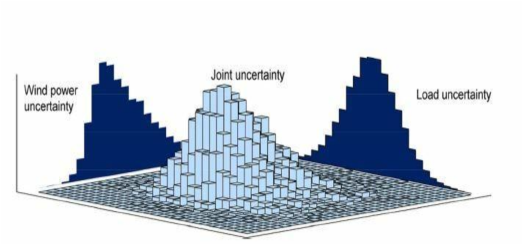

Fig:4- Uncertainties in AC microgrid of [25]

The local energy management system (EMS) of a microgrid is mostly associated with the distributed generators' operation. Battery energy storage (BES) system is an integral part of renewable distributed generators as they regulate the intermittent nature of the renewable resources. So, BES system is very important for the stability of a microgrid. Photovoltaic (PV) power generation is preferred for small DC distribution networks because of their ability to generate DC power directly from solar irradiation. PV generation needs to be constantly forecasted for planning purposes. However, this forecasting needs to be accurate from the stability perspective as any kind of prediction error influences the energy storage device directly. However, PV power forecasting comes with the challenges of natural variation in solar irradiation and volatility during dawn and dusk. Extreme learning machine (ELM) has gained popularity for PV power prediction recently [26]. However, ELM is computationally complex because of the batch mode operation. As PV power generation in predicted over a short period of time, any prediction scheme needs to satisfy the two criteria: computational time and online operation. Keeping this in mind, a kernel-based online sequential ELM (OSELM) algorithm has been developed in [27]. This algorithm which is computationally fast and reduces prediction error robustly is termed fast reduced Morlet kernel-based OSELM (FR-MKOSELM). The effectiveness of the proposed scheme is measured in terms of root mean square error (RMSE), mean absolute error (MAE), symmetric mean absolute percentage error (SMAPE), execution time and the square of correlation coefficient (CC2). When compared to other ELM methods, the proposed method performs the best in all aspects except execution time. In terms of execution time, its slower than only the regular OSELM. Overall, the FR-MKOSELM method proves to be better than the other comparable ELM techniques. This FR-MKOSELM method, coupled with improved secondary control, ensures better performance of the battery management system (BMS) is terms of temperature control, battery life, power loss and state of charge (SoC).

4. PREDICTIVE APPLICATIONS

United States have faced some serious natural disasters in recent years. Any severe weather-related incident is a huge detriment to the society in general and power grid is not outside the scope of it. Components of the power grid become damaged and system outage occurs. If the outage of the components can be predicted prior to any severe weather events, a lot of damage can be mitigated by developing efficient prevention and recovery techniques [28]. So, accurate prediction of outages before an imminent natural hazard can make the grid more robust, saving a lot of money in the process. In [29], the authors have proposed a machine learning based solution to this problem, especially in the case of hurricanes. The proposed algorithm is based on logistic regression. In this approach, a decision boundary is drawn using the logistic regression to classify every component of the grid in one of the following two categories: operational and damaged. The regression line is a second order polynomial with two variables: wind speed and distance from the center. The probability of a component being damaged increases with higher wind speed and lower distance. The coefficients of the regression line are calculated by minimizing the cost function. Once the decision boundary has been formed, all the components can be classified as either operational or damaged. Finally, after the occurrence of the extreme weather event, the efficacy of the proposed algorithm is calculated using a F1 score between 0 and 1, which is based on precision and recall metrics calculated from the confusion matrix. A higher F1 score represents a better prediction. The presented case study in this work demonstrated the proposed algorithm to have acceptable level of performance (F1 score of .9027). However, this method has not been found to be tested for any real-life scenario so far, as known.

Quality of the collected raw data is a very important factor for accurate prediction. The work in [30] devises a method for predicting missing data from power transformers in a power grid. The frequency of missing data is quite high because of severe working conditions. The content of representative hydrocarbon gases is indicative of the state of a power transformer and this paper deals with predicting the state of these gases from missing data. Two cases of missing data are discussed in this paper: single missing data and consecutive missing data. This developed framework, termed OR_MLF, is a combination of preprocessing of collected data, optimized support vector machine (OSVM), and refined support vector machine (RSVM). At first, the collected data is preprocessed, and a basic predictor is developed using traditional support vector machine (SVM). After that, a new training dataset is extracted from the basic predictor and it is used to develop OSVM predictor. Finally, the output from the OSVM is used to obtain the RSVM predictor. This OR_MLF framework is finally tested and compared against traditional machine learning techniques like nearest neighbor (NN), regular SVM, and least square support vector machine (LSSVM). OR_MLF outperforms the other traditional methods in minimizing the mean square error (MSE) in predicting the contents of the representative hydrocarbon gases in a power transformer, for both single missing data and three consecutive missing data. The result also proves the obvious: OR_MLF with RSVM is a better predictor than OR_MLF with just OSVM.

Renewable energy resources are inherently volatile. So, accurate prediction of renewable energy generation augurs well for the system. Machine learning based nowcasting and forecasting methods for photovoltaic power generation are developed and compared in [31], the main difference between nowcasting and forecasting being the time frame of the prediction. In this work, nowcasting is done 1 hour ahead for real time control and forecasting is done 1 to 7 days ahead for operational management. All the methods are based on data generated by energy management system (EMS) of the smart polygeneration microgrid (SPM) deployed in University of Genova, Savona campus. In this work, three methods: kernelized regularized least squares, extreme learning machine (ELM), and random forest (RF) are compared in terms of their performance. These three methods are representatives of three broad categories of machine learning techniques: kernel methods, neural network, and ensemble methods, respectively. All these methods, along with the traditional method of prediction, are compared in terms of mean absolute error (MAE), mean square error (MSE), normalized mean square error (NMSE), relative error percentage (REP), and Pearson product-moment correlation coefficient (PPMCC). All the data-driven machine learning based methods show significant improvement over traditional method of generation prediction, based on the meteorological data and physical model of the microgrid. The nowcasting results are always more accurate than forecasting results, because of the time frame and associated less randomness. Machine learning methods demonstrate better performance in all the possible scenarios. However, the performance gets better with larger amount of data and smaller prediction time span. Among the machine learning based methods, random forest performs best in terms of reducing the prediction error. Last but not the least, machine learning based methods show significant improvement over the actual method (AM) in terms of predicted savings and carbon di-oxide emission. Time series forecasting of energy generation and consumption is gaining popularity because of the availability of data and advancements made in computational power of machines and they are explored in [32-37].

5. GAME THEORY APPLICATIONS

In [38], the authors have proposed a game-theoretic novel demand side management technique to integrate intermittent wind energy efficiently. This proposed method aims to adjust controllable loads to match supply and demand, so that the dependence on fast responding thermal generators can be minimized and total energy cost can be reduced. An isolated microgrid with several end users, one wind turbine and one conventional generator has been used for analysis and it is demonstrated in fig.5.

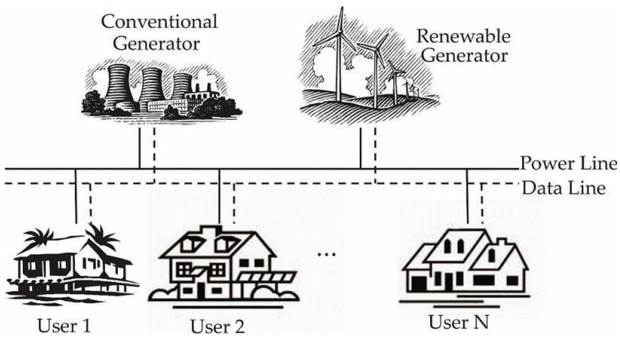

Figure 5 Isolated microgrid model in [32]

A dynamic potential game model has been developed where all the end users act as players. All the players are rational, and their strategy is to establish the optimum load profile for each time slot. The payoff for each player is their electricity bill, which they aim to minimize. Scenarios with single user, two users and generalized case have been analyzed to find out optimum load scheduling strategy. In the single user case, backward induction technique has been used to find out the optimum load scheduling. The two-users case was modeled as an ordinal potential game, Nash equilibrium (NE) was derived and it proved to be the optimum strategy. NE represents the best strategy for the generalized case also. As the wind power generation is a stochastic process, it is modeled as a Markov chain with six states and the transition probability matrix is developed by collecting data for six months in west Texas. With the help of numerical simulation, it is demonstrated that this proposed demand side management technique saves 38% of the total generation cost. If the wind power generation could be predicted perfectly, a further 21% can be saved. Moreover, this proposed method reduces the electricity bills of the end users. One drawback of this work is that the cost sharing model for each user does not depend on instantaneous load of each user, rather the total load over all time slots. This makes the game-theoretic formulation less complex, however it does not capture the load fluctuations properly.

Another alternative to tackle the intermittency of renewable energy resources is trading of energy among microgrids, which has been studied in [39]. In a multi-microgrid system, every microgrid acts as a player and they can trade energy depending on whether they have surplus or deficit. Also, this trading mechanism needs to be fair and microgrids need to have incentives for trading energy. All these issues have been incorporated in this work, where a game-theoretic solution is proposed. This work stands out from the previous related works as it introduces a seller level game and proposes a simple pricing mechanism which helps to decrease the communication overhead. Two aggregator agents, buyer aggregator agent (BAA) and seller aggregator agent (SAA), operate on behalf of buyers and sellers, respectively. Microgrids with energy deficiency register with BAA. In case any deficient microgrid cannot satisfy demand by trading with neighboring microgrids, then the remaining demand must be satisfied by buying energy from the main grid. Based on the deficit and price of buying and selling from the main grid, BAA fixes the optimal bid value to purchase from the seller microgrids. Based on the bid value, seller microgrids might adjust its own demand and inform the SAA about the amount available for selling. SAA the aggregates the information from all the sellers and relays the information to BAA. Upon receiving this information from BAA, the buyer microgrids choose the optimum strategy, which is normally the Nash equilibrium, and send the request to energy market operator (EMO). Upon further verification, EMO allocates the available energy to prospective buyers based on their priority factor. The priority factor ensures that trading is incentivized. When compared to the multi leader multi follower (MLMF) and baseline distribution mechanisms, the numerical results demonstrate the superiority of the proposed method in generating revenue for sellers and minimizing the difference between required and allocated energy for the buyers. This proposed method also eliminates selfish behavior of buyer microgrids.

A cooperative game-theoretic method has been developed in [40] to distribute the operational benefits to different components of a microgrid that would ensure global efficiency and individual rationality. Different coalitions can be formed among the components of a microgrid and all the coalitions would strive to maximize its characteristic function. The characteristic function is the value assigned to a coalition to represent the benefits. Shapley value is used to indicate the importance of a member in a coalition and benefit is distributed according to Shapley values. Numerical simulations indicate that forming larger coalitions increases overall benefits, as opposed to forming smaller coalitions. Decreased volatility of renewable power sources, increased energy storage capacity and increased amount of transferable loads impact the total benefit positively. However, energy storage and transferable loads have a reciprocating relationship with the importance of conventional generators.

Microgrid is a great solution for integrating distributed renewable energy sources. Renewable energy sources are clean; however, their installation is expensive. That is why their integration needs to incorporate a balance between higher cost and lower pollution. This problem can be formulated as a dual objective optimizing problem, with the objective functions being exhaust gas and fuel cost. This line of inquiry has been performed in [41, 42] using a game theory-based approach. This method can find out the equilibrium point of optimum strategies with the help of impact factor and clustering. The numerical simulation demonstrates that the equilibrium point would reduce the pollution by 3.47% in exchange of increasing the fuel cost 0.47%, which is very reasonable. This method is less subjective, as compared to other related techniques. However, the biggest drawback of this method is large amount of calculation. Consequently, it can be applied only in small scale microgrids.

Modern grids are prone to cyber-attacks and they need to be equipped with several security mechanisms like Virtual Private Network (VPN), firewall etc. Optimal heterogeneous allocation of the security mechanisms to improve the grid tolerance against the cyber-attacks using a graph coloring method has been proposed in [43]. In [44], authors have developed a game theoretic framework to model the various attack paths and how they can affect grid contingency scenarios. This framework can also identify the most critical substation and help the operator to select the most appropriate defense mechanism.

6. CONCLUSION AND FUTURE WORK

To summarize the application of machine learning and game theory in microgrid research, a dual perspective may be exercised from the angles of addressing the challenges associated with microgrid and the use of various machine learning algorithms in systematic pipelines that comply with the domain knowledge of power systems, microgrid and distributed generation. This review gleefully finds that various major machine learning algorithms including some advanced ones are used to address well-recognized microgrid issues even though both microgrid and machine learning are relatively new research areas. It is noticed that for different purposes or applications, different machine learning techniques out-perform the competing algorithms; however, it remains to be a vastly open research area given the fact that feature extraction and feature engineering itself leaves plenty of room for optimization for different power systems and microgrid scenarios before the extracted features are fed to respective machine learning algorithms for highest accuracy, optimal response time and economic computation. While some of the proposed models promote dynamic decision-making at the edge device or equipment through machine learning algorithms, an end-to-end system approach with hardware-software integration for real-time control and response of microgrid and grid equipment are yet to be explored. As far as machine learning algorithms are concerned, the ensemble methods-especially, random forest (RF), seem to have offered significantly better performance in many of the microgrid scenarios; but more recent and advanced deep learning techniques like generative adaptive network (GAN) and reinforced learning are yet to be exercised and apparently will need the aforementioned cohesion between software-hardware measurement, control and real-time response. Based upon the established phenomenon of microgrid and power systems, some transfer learning techniques may be explored for various applications. This review also includes a brief survey of game theoretic applications in microgrid. Game theory is an interesting option to tackle various issues related to microgrid. However, machine learning is likely to prevail as the more wholesome alternative.

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