A Review of Machine Learning in Energy Management of Power Systems

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Abstract

This literature review studies machine learning applications in energy management and demand response in the power systems industry. Power systems is a field of engineering that is starting to welcome machine learning (ML) to advance data-driven modeling, prediction and forecasting. There are a variety of ML models used for power systems, although a large proportion published uses deep reinforcement learning (DRL). This review will explore a variety of models and discuss whether DRL is the most appropriate model for an uncertain, non-linear, time-dependent problem such as energy management. This paper explores ways in which machine learning can be applied to energy management, comparing and recommending certain techniques, and supporting that machine learning has a future in the power systems industry. By finding ways to minimize electricity usage from the grid, machine learning can help accelerate the development of climate change solutions.

Keywords: machine learning, power systems, energy management, demand response, deep reinforcement learning

1 Introduction

The power systems industry is undergoing a significant transformation, moving away from traditional grid-to-consumer models towards more decentralized and dynamic systems. This shift has caused power generation and distribution to become less predictable [1], highlighting the need for improved models to forecast energy supply and demand. Traditional power control systems relied on mathematical models based on static historical patterns [2]. These models cannot handle the large amounts of real-time data generated by modern measurements and rapid changes in the electricity markets' business models. Real-world energy demand is influenced by highly non-linear, complex and uncertain factors - such as weather, small-scale generation, renewables, and the recent shift towards electrification - which are challenging to capture using these traditional models [3].

Similarly, energy supply has become more unpredictable and decentralized, introducing new challenges in modelling output. Solar and wind energy are highly variable, with their output being directly tied to weather, which is already difficult to forecast. Renewable energy sources are also being deployed on much smaller scales [1], with private individuals installing solar and storage energy systems at home. This results in a significantly more complex energy production landscape, with highly decentralized and variable energy sources contributing to the grid.

This has also resulted in a massive increase in available grid data [2], with sensors and smart meters collecting data with a high temporal resolution, and other relevant data, such as weather, societal factors predictive of energy consumption, and pricing signals.

The increased complexity requirements, data availability, and decreased compute costs have set the stage for ML models to be applied to modern power control systems [2], [4]. ML models have several advantages over rule-based models, such as having the ability to capture complex non-linear relationships and interactions, being effective in using large and diverse historical and real-time data sources, and being capable of dynamically adjusting themselves based on real-time data [5].

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There are limitations to the use of ML models in managing electrical grids, especially computation speed of models, inability to work on legacy infrastructure, and lack of transparency for regulatory body clearance. In a real-time system that requires performing real-time control, high-performing and complex ML models need to have fast computational speeds [1]. Next, utility companies often operate on a foundation of legacy equipment which may require large investments to replace with modernized equipment capable of running ML models. Lastly, models which are difficult to interpret, also described as "black box" [7], raise safety challenges with regulatory bodies in the utilities industry, and present scalability issues [8].

This literature review will explore how ML models are currently used in power control systems and identify and contrast the suitability of model types for different applications in power control systems. The paper is organized as follows. Section II presents the ML models used in the reviewed papers for energy management, and the gain in performance from the usage of those models. Section III discusses which models are most suitable to specific goals of power system performance. Section IV concludes the paper and discusses promising directions of future work.

2 Review of Machine Learning Models Used in Power Systems Publications

2.1 Support Vector Machine

Support Vector Machine (SVM) was used in failure prediction of a smart grid in [5], which is a suitable model for a supervised learning problem with a historical database and physical measurements indicating upcoming black-outs. SVM was also used by Manohar and Koley [6] and in many other papers for fault detection [5], works well with high-dimensionality data [9] and in classification problems [7], thus it can be concluded that SVM is suited to fault detection.

Electricity distribution grids, including microgrids, are inherently prone to faults, which occur when powered lines short to the ground or to each other. Such events can lead to partial or complete loss of electrical power in the affected grid [5]. The ability to detect, predict, and classify these faults is critical for maintaining grid stability and preventing outages.

One of the SVM papers studied for fault detection was published by Gupta et al. [5]. The input data into the SVM model was a statistical distribution of normal operation and blackout occurrences of the grid studies, including the changes in the distribution from Gaussian to non-Gaussian when a line fault occurs. The paper applied three kernels, namely RBF, polynomial and sigmoid, and concluded that RBFs are the most suitable kernel, with the highest training and validation accuracy. Cross-validation is then conducted to find the best parameters. The result of using SVM is 100% training and testing accuracy on predicting blackouts, showing promising results in using SVM for data with patterns similar to fault patterns in power systems.

SVM was used again by Manohar and Koley [6]. Their model achieved a remarkable fault classification accuracy of 95%, correctly categorizing 3 phase electrical grid faults into one of four types: shunt faults, single line-to-ground faults, double line-to-ground faults and three-phase faults. The model performed with a 98% accuracy in identifying the specific section of the grid where the fault occurred. These results again demonstrate the suitability of SVMs in fault detection and classification.

2.2 Random Forest

Random Forest was used by Xuan et al. [10] for feature selection of input features of a power system load dataset, before being used to train a neural network. The authors used a random forest model since they are not sensitive to multivariate common linearity, are robust to missing and unbalanced data, and can identify relationships between thousands of features, which makes random forests a high-performing feature selection algorithm [10]. Their feature selection approach improved overall model performance compared to other methods when used with convolutional neural networks. The promising results of ML-based feature selection further support machine learning's utility in power systems, where limited computing capacity encourages the use of cleaner datasets and simpler models. Al Karim et al. [11] further support the utility of random forests in feature selection.

The positive results of feature selection highlighted in this paper shows that feature selection is imperative in power systems applications [12], since computational cost, time and complexity directly relates to the computing capacity and interpretability issues discussed in the previous section.

Similarly, the output from a random forest model was also utilized as input for a separate model designed to optimize the scheduling of standalone microgrids [13]. In this study, ML was combined with a more traditional linear programming model resulting in prediction errors of 5%, 1%, and 2% for total cost, voltage deviation, and power loss respectively. This showcases how ML techniques don't need to completely replace previous methods to improve scheduling performance.

2.3 Neural Networks

The study of Xuan et al. [10] used neural networks after feature selection was done with random forest as described above. Xuan et al. leveraged convolutional neural networks (CNN) combined with a bidirectional gated recurrent unit (BiGRU), arguing that deep learning methods are well suited for processing time-series data. Their results showed that their CNN-BiGRU method outperformed other techniques, namely CNN-NN, CNN-GRU, LSTM, and CNN-LSTM, when measured by both Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) metrics, on multiple datasets. The authors emphasized CNNs' ability to capture local spatial patterns in time-series data, and the integration with BiGRU allowed their model to integrate both spatial and temporal relationships, which ultimately lead to more accurate load forecasting results.

The use of CNNs enables the model to extract additional features by using convolutional layers that share weights and process local spatial information. This decreases dimensionality by reducing the number of input parameters to the consequent fully connected layers. Reducing dimensionality with convolutional layers lowers computational costs, an important factor in power systems with limited computing capacity as discussed previously. All these benefits from CNNs provide support for their application in load forecasting in a power system.

Neural networks were also employed by Venayagamoorthy et al. [14] for microgrid management. Microgrid management involves assessing current electrical loads and energy sources to make decisions such as importing electricity from the commercial grid, activating diesel generators, electrical battery charging, and predicting critical load levels. Their study compared decision trees and neural network-based models on their ability to fulfill critical load demands, maximize the use of renewable energy, and extend battery life by optimizing charging and discharging cycles.

The results demonstrated that both models successfully fulfilled critical load demands. However, the neural network-based model outperformed the decision tree-based model in two aspects. First, it relied less on electricity from diesel generators and from the commercial electrical grid, indicating more efficient use of renewable energy usage. Second, the neural network model exhibited smoother switching behavior between energy sources, compared to the rapid switching behavior observed in the decision tree model. This smoother operation contributes to the overall stability and efficiency of microgrid management and also prolongs life of electrical batteries.

An artificial neural network (ANN) was used again in [13] together with reinforcement learning (RL) for another analysis of demand response, specifically for home energy management. The end-goal of the two-tiered model is for optimal scheduling of controllable loads to minimize energy consumption and costs. The neural network is used in the first step of predicting electricity prices in the hour-ahead future, before a RL model is created for decision-making executed by each home appliance.

Using ANN, the electricity price prediction had a low error; the Mean Absolute Error (MAE) of the ANN model was 2.12, and the Mean Absolute Percentage Error (MAPE) was 8.59 [13]. This shows that ANN models are well-suited to price forecasts in demand response programs - a keystone in the future initiatives of maximizing energy and minimizing costs.

2.4 Reinforcement Learning

Next, Reinforcement Learning (RL) was used in [13] along with the original data set and the predicted electricity cost output from the ANN model. RL uses the concepts of state, rewards and actions for decision making. The model implemented the popular RL Q-learning technique to enable each agent - each home appliance - to learn the optimal policy for energy consumption.

The results of the final ANN-RL model were compared with the results of a Mixed-Integer Linear Programming (MILP) on the same dataset. The former resulted in daily lower electricity costs after its learning phase has elapsed, compared to MILP which does not learn. Furthermore, the computational time of training the ANN-RL model was low at 1 minute and 20 seconds, exemplifying its suitability for real-time applications such as in power systems.

Although this paper did not consider the uncertainties of appliance usage patterns, the results of the ANN-RL methods are promising, and neural networks have been shown to be able to account for uncertainty in power systems applications [1]. A DRL approach may be better suited for uncertain problems, as discussed next.

Bahrami et al. [3] explored the use of DRL models for load scheduling in microgrids. Load scheduling involves designating specific times for running household appliances, such as electric vehicle (EV) charging, dishwashers, and heating systems, to optimize energy usage. The Markov decision process was used within the DRL model, which is especially useful to model uncertainties in many power system problems [15]. The variables with uncertainties were electricity price, load demand, and users' discomfort cost, which was modeled with state transitions in the MDP. The DRL model defines state as the household load and electricity price, action as the load demand to be scheduled, and reward as balancing electricity cost reductions with minimizing user inconvenience.

The study focused on a decentralized approach, where the DRL model was installed in individual households to manage local loads. This contrasts with centralized models, which are deployed at the energy source to manage loads across multiple households. The decentralized DRL model was compared against Actor-Critic Method, Q-Learning, and Double Q-Learning centralized methods, which are often used in power system studies [16].

The results demonstrated that the decentralized DRL model achieved a 33% reduction in peak loads and a 13% cost savings compared to the centralized models. The decentralized approach showed faster convergence when compared to centralized methods, highlighting its efficiency and practicality for localized energy management in microgrids.

3 Analysis and Comparison of ML Models

From the above papers and ML models reviewed, it is clear that ML is highly applicable in the field of electrical grid and energy management. The application of various models was reviewed, with specific models having clear advantages in specific prediction applications.

Most successful ML models in power systems applications are non-parametric, which handle non-linearities better than parametric models [10]. Parametric models require high stability of original data processing and time series and do not perform well with nonlinear factors, which is contrary to most data gathered in power systems.

In the section discussing neural network models, Venayagamoorthy et al. [14] compared an NN based model for microgrid management to a decision tree based model and discovered neural networks are superior for managing. The NN model excelled at minimizing use of non-renewable energy sources and also has less abrupt energy source switching behavior which is favorable in prolonging battery life. This supports the idea that neural network based models may be better suited for management of microgrids.

DRL is highly valuable for energy management in microgrids and demand response (DSR) contexts. It helps decide when to charge or discharge energy storage devices, import power from commercial grids, or activate diesel generators. With a reward function in DRL models, users can tweak the function to prioritize goals like reducing reliance on non-green energy or prolonging battery life, making DRL adaptable to personal preferences and encouraging its adoption.

In DSR, where end-users adjust electricity usage based on grid conditions like dynamic pricing, DRL simplifies real-time energy consumption decisions. It lowers barriers to DSR adoption, maximizes cost savings, and improves grid performance [3].

In the section on SVMs, multiple papers highlight its usefulness in detecting faults in an electrical grid [5], [6], [7], [8]. SVMs often excel in fault detection due to their ability to learn quickly from small datasets and their low computational cost [9], [8]. Fault detection is essentially a form of outlier detection, as faults represent anomalies during the normal operation of a microgrid. Since faults are rare, datasets containing fault examples are typically small. Neural networks, by contrast, require large datasets to perform well, as they rely on extensive data to learn patterns. With limited data, their performance declines. SVMs are well-suited to small datasets and can effectively identify faults, making them the better choice in such cases [8].

This is further supported by Vadana and Kottayil who conducted a comparative study of SVM and NN for microgrid management [17]. Their study focused on models deciding when to charge and discharge pumped-storage hydroelectric systems and electrical batteries. The models tested in the study were an SVM and an NN. The results showed that the SVM outperformed the NN in terms of accuracy of predicting what energy sources to charge or discharge, achieving 97.52%, compared to the ANN's 90.1%. The NN models used in this study were simple, consisting of only 1 to 2 hidden layers with 6 to 20 neurons per layer. Furthermore, the datasets used for training are around 302 examples big, with a 80:20 split used for training and validation. The performance of the NN could be significantly improved with more complex architectures or larger hidden layer sizes and larger datasets.

4 Conclusion

This literature review examines the viability of machine learning models for managing power systems, with specific applications on demand response, microgrids and fault detection. The publications reviewed demonstrate how different ML techniques are being developed and applied in this domain. The ML methods examined in this paper include Tree-Based Models, Neural Networks, Support Vector Machines, and Deep Reinforcement Learning. The main takeaways are: SVMs have demonstrated excellent performance in fault detection in scenarios with limited data; NNs are better suited for management tasks, provided they use large datasets for training; and DRL is able to learn and adapt dynamically, making it useful in complex, real-time management and optimization scenarios. The findings suggest that machine learning provides a robust and flexible toolkit for addressing the challenges of power system management. Future research should focus on addressing the challenges of real-time computational complexity and model interpretability in ML. These two areas are critical in pushing ML from publications into physical prototypes which can handle the computation requirements, and conceivably be accepted by regulatory bodies and implemented in small-scale test grids.

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