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RESEARCH OF FAULT DETECTION FOR THREE TYPES OF WIND TURBINES SUBSYSTEM USING MACHINE LEARINING

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ABSTRACT

Smart home energy management systems help the distribution grid operate more efficiently and reliably, and enable effective penetration of distributed renewable energy sources. These systems rely on robust forecasting, optimization, and control/scheduling algorithms that can handle the uncertain nature of demand and renewable generation. This paper proposes an advanced ML algorithm, called Recurrent Trend Predictive Neural Network based Forecast Embedded Scheduling (rTPNN-FES), to provide efficient residential demand control. rTPNN-FES is a novel neural network architecture that simultaneously forecasts renewable energy generation and schedules household appliances. By its embedded structure, rTPNN-FES eliminates the utilization of separate algorithms for forecasting and scheduling and generates a schedule that is robust against forecasting errors. This paper also evaluates the performance of the proposed algorithm for an IoT-enabled smart home. The evaluation results reveal that rTPNN-FES provides near-optimal scheduling 37.5 times faster than the optimization while outperforming state-of-the-art forecasting techniques.

Keywords: energy management, forecasting, scheduling, neural networks, recurrent trend predictive neural network

INTRODUCTION

Residential loads account for a significant portion of the demand on the power system. Therefore, intelligent control and scheduling of these loads enable a more flexible, robust, and economical power system operation. Moreover, the distributed nature of the local residential load controllers increases system scalability. On the distribution level, the smart grid benefits from the increased adoption of residential demand and generation control systems, because they improve system flexibility, help to achieve a better demand-supply balance, and enable increased penetration of renewable energy sources. Increasing flexibility of the building energy demand depends on multiple developments, including accurate forecasting and effective scheduling of the loads, incorporation of renewable energy sources such as solar and wind power, and integration of suitable energy storage technologies (e.g. batteries and/or electric vehicle charging) into the building energy

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management system. Advanced control, optimization and forecasting approaches are necessary to operate these complex systems seamlessly In this paper, in order to address this problem, we propose a novel embedded neural network architecture, called Recurrent Trend Predictive Neural Network based Forecast Embedded Scheduling (rTPNN-FES), which simultaneously forecasts the renewable energy generation and schedules the household appliances (loads). rTPNN-FES is a unique neural network architecture that enables both accurate forecasting and heuristic scheduling in a single neural network. This architecture is comprised of two main layers: 1) the Forecasting Layer which consists of replicated Recurrent Trend Predictive Neural Networks (rTPNN) with weight-sharing properties, and 2) the Scheduling Layer which contains parallel softmax layers with customized inputs each of which is assigned to a single load. In this paper, we also develop a 2-Stage Training algorithm that trains rTPNN-FES to learn the optimal scheduling along with the forecasting. However, the proposed rTPNN-FES architecture does not depend on the particular training algorithm, and the main contributions and advantages are provided by the architectural design. Note that the rTPNN model was originally proposed by Nakıp et al. [1] for multivariate time series prediction, and its superior performance compared to other ML models was demonstrated when making predictions based on multiple time series features in the case of multi-sensor fire detection. On the other hand, rTPNN has not yet been used in an energy management system and for forecasting renewable energy generation. Furthermore, the advantages of using rTPNN-FES instead of a separate forecaster and scheduler are in three folds: 1. rTPNN-FES learns how to construct a schedule adapted to forecast energy generation by emulating (mimicking) optimal scheduling. Thus, the scheduling via rTPNN-FES is highly robust against forecasting errors. 2. The requirements of rTPNN-FES for the memory space and computation time are significantly lower compared to the combination of a forecaster and an optimal scheduler. 3. rTPNN-FES proposes a considerably high scalability for the systems in which the set of loads varies over time, e.g. adding new devices into a smart home Internet of Things (IoT) network. We numerically evaluate the performance of the proposed rTPNN-FES

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architecture against 7 different well-known ML algorithms combined with optimal scheduling. To this end, publicly available datasets [2, 3] are utilized for a smart home environment with 12 distinct appliances. Our results reveal that the proposed rTPNN-FES architecture achieves significantly high forecasting accuracy while generating a close-to-optimal schedule over a period of one year. It also outperforms existing techniques in both forecasting and scheduling tasks

RELATED WORKS In this section, we present the comparison of this paper with the-state-of-the art works in three categories: 1) The works in the first category develop an optimization-based energy management system without interacting with ML. 2) The works in the second category focus on forecasting renewable energy generation using either statistical or deep learning techniques. 3) The works in the last category develop energy management systems using ML algorithms.

Optimization-based Energy Management Systems We first review the recent works which developed optimization-based energy management systems. In [4], Shareef et al. gave a comprehensive summary of heuristic optimization techniques used for home energy management systems. In [5], Nezhad et al. presented a model predictive controller for a home energy management system with loads, photovoltaic (PV) and battery electric storage. They formulated the MPC as a mixed-integer programming problem and evaluated its economic performance under different energy pricing schemes. In [6], Albogamy et al. utilized Lyapunov-based optimization to regulate HVAC loads in a home with battery energy storage and renewable generation. In [7], S. Ali et al. considered heuristic optimization techniques to develop a demand response scheduler for smart homes with renewable energy sources, energy storage, and electric and thermal loads. In [8], G. Belli et al. resorted to mixed integer linear programming for optimal scheduling of thermal and electrical appliances in homes within a demand response framework. They utilized a cloud service provider to compute and share aggregate data in a distributed fashion. In [9], variants of several heuristic optimization methods (optimal stopping rule, particle swarm optimization, and grey wolf optimization) were applied to the scheduling of home appliances under a virtual power plant framework for the distribution grid. Then, their performance was compared for three types of homes with different demand levels and profiles. There is a wealth of research on optimization and model predictive controller-based scheduling of residential loads. In this literature, usually, prediction of the load demand and generation (if available) are pursued independently from the scheduling algorithm and are merely used as a constraint parameter in the optimization problem. The discrepancy in predicted and observed demand and generation may lead to poor performance and robustness issues. The proposed rTPPN-FES in this paper handles forecast and scheduling in a unified way and, therefore, provides robustness in the presence of forecasting errors.

Forecasting of Renewable Energy Generation We now briefly review the related works on forecasting renewable energy generation, which have also been reviewed in more detail in the literature, i.e. [10, 11]. The earlier research in this category forecast energy generation using statistical methods. For example, in [12], Kushwaha et al. use the well-known seasonal autoregressive integrated moving average technique to forecast the PV generation in 20-minute intervals. In [13], Rogier et al. evaluated the performance of a nonlinear autoregressive neural network on forecasting the PV generation data collected through a LoRa-based IoT network. In [14], Fentis et al. used Feed Forward Neural Network and Least Square Support Vector Regression with exogenous inputs to perform short-term forecasting of PV generation. In [15] analyzed the performances of (Autoregressive Integrated Moving Average) ARIMA and Artificial Neural Network (ANN) for forecasting the PV energy generation. In [16], Atique et al. used ARIMA with parameter selection based on Akaike information criterion and the sum of the squared estimate to forecast PV generation. In [17], Erdem and Shi analyzed the performance of autoregressive moving averages to forecast wind speed and direction in four different approaches such as decomposing the lateral and longitudinal components of the speed. In [18], Cadenas et al. performed a comparative study between ARIMA and nonlinear autoregressive exogenous artificial neural network on the forecasting wind speed. The recent trend of research focuses on the development of ML and (neural network-based) deep learning techniques. In [19], Pawar et al. combined ANN and Support Vector Regressor (SVR) to predict renewable energy generated via PV. In [20], Corizzo et al. forecast renewable energy using a regression tree with an adopted Tucker tensor decomposition. In [21] forecast the PV generation based on the historical data of some features such as irradiance, temperature and relative humidity. In [22], Shi et al. proposed a pooling-based deep recurrent neural network technique to prevent overfitting for household load forecast. In [23], Zheng et al. developed an adaptive neuro-fuzzy system that forecasts the generation of wind turbines in conjunction with the forecast of weather features such as wind speed. In [24], Vandeventer et al. used a genetic algorithm to select the parameters of SVM to forecast residential PV generation. In [25], van der Meer et al. performed a probabilistic forecast of solar power using quantile regression and dynamic Gaussian process. In [26], He and Li have combined quantile regression with kernel density estimation to predict wind power density. In [27], Alessandrini et al. used an analogue ensemble method to problematically forecast wind power. In [28], Cervone et al. combined ANN with the analogue ensemble method to forecast the PV generations in both deterministic and probabilistic ways. Recently in [29], Guo et al. proposed a combined load forecasting method for a Multi Energy Systems (MES) based on Bi-directional Long Short-Term Memory (BiLSTM). The combined load forecasting framework is trained with a multi-tasking approach for sharing the coupling information among the loads. Although there is a significantly large number of studies to forecast renewable energy generation and/or other factors related to generation, this paper differs sharply from the existing literature as it proposes an embedded neural network architecture called rTPNN-FES that performs both forecasting and scheduling simultaneously

Machine Learning Enabled Energy Management Systems In this category, we review the recent studies that aim to develop energy management systems enabled by ML, especially for residential buildings. The first group of works in this category used scheduling (based on either optimization or heuristic) using the forecasts provided by an ML algorithm. In [30], Elkazaz et al. developed a heuristic energy management algorithm for hybrid systems using an autoregressive ML for forecasting and optimization for parameter settings. In [31], Zaouali et al. developed an auto-configurable middle-ware using Long-Short Term Memory (LSTM) based forecasting of renewable energy generated via PV. In [32], Shakir et al. developed a home energy management system using LSTM for forecasting and Genetic Algorithm for optimization. In [33], Manue et al. used LSTM to forecast the load for battery utilization in a solar system in a smart home system. In [34] developed a hybrid system of renewable and grid-supplied energy via exponential weighted moving average-based forecasting and a heuristic load control algorithm. In [35],

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Aurangzeb et al. developed an energy management system which uses a convolutional neural network to forecast renewable energy generation. Finally, in [36], in order to distribute the load and decrease the costs, Sarker et al. developed a home energy management system based on heuristic scheduling. The second group of works in this category developed energy management systems based on reinforcement learning. In [37], Ren et al. developed a model-free Dueling-double deep Q-learning neural network for home energy management systems. In [38], Lissa et al. used ANN-based deep reinforcement learning to minimize energy consumption by adjusting the hot water temperature in the PV-enabled home energy management system. In [39], Yu et al. developed an energy management system using a deep deterministic policy gradient algorithm. In [40], Wan et al. used a deep reinforcement learning algorithm to learn the energy management strategy for a residential building. In [41], Mathew et al. developed a reinforcement learning-based energy management system to reduce both the peak load and the electricity cost. In [42], Liu et al. developed a home energy management system using deep and double deep Q-learning techniques for scheduling home appliances. In [43], Lu et al.

developed an energy management system with hybrid CNN-LSTM based forecasting and rolling horizon scheduling. In [44], Ji et al. developed a microgrid energy management system using the Markov decision process for modelling and ANN-based deep reinforcement learning for determining actions. Deep learning-based control systems are also very popular for off-grid scenarios, as off-grid energy management systems are gaining increasing attention to provide sustainable and reliable energy services. In References [45] and [46], the authors developed algorithms based on deep reinforcement to deal with the uncertain and stochastic nature of renewable energy sources. All of these works have used ML techniques, especially deep learning and reinforcement learning, to build energy management systems. Moreover, in a recent work [47], Nakıp et al. mimicked the scheduling via ANN and developed an energy management system using this ANN-based scheduling. However, in contrast with rTPNN-FES proposed in this paper, none of them has used ANN to generate scheduling or combined forecasting and scheduling in a single neural network architecture

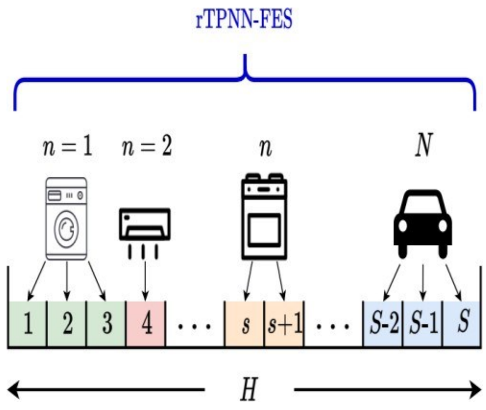

Figure 1: The illustration of the system considered by rTPNN-FES

LITERATURE REVIEW:

IN "LIU, B., LUND, J.R., LIAO, S., JIN, X., LIU, L., CHENG, C.: OPTIMAL POWER PEAK SHAVING USING HYDROPOWER TO COMPLEMENT WIND AND SOLAR POWER UNCERTAINTY. ENERGY CONVERSION & MANAGEMENT 209(APR.) (2020) 112628.1–112628.15" Booming renewable energy development, such as wind and solar power, with their intermittency and uncertainty characteristics, pose challenges for power grid dispatching, especially for power grid peak shaving. In this paper, coordinated operation of hydropower and renewable energy in a provincial power grid is explored to alleviate fluctuation and aid peak shaving. Considering their aggregate effect, this study aggregates wind power plants and solar power plants into a virtual wind power plant and a virtual solar power plant, respectively, and the forecasted error distribution of wind and solar power is analyzed with kernel density estimation. Then, based on the principles of using hydropower to compensate for fluctuating wind and solar power, a day ahead peak shaving model with the objective of minimizing residual load peak-valley difference is built, which introduces chance constraints for forecast errors and coordinate hydropower operation with wind and solar power. To simplify the solution, the proposed model is recast as a successive linear programming problem. Day-ahead scheduling case studies of a provincial power grid system indicate that the proposed model can conduct peak shaving effectively, hydropower can compensate wind and solar power fluctuation, improve the stability of combined output, and make better use of renewable energy. Therefore, this study provides an alternative approach for peak shaving operation of power system with hydropower and increasing integration of wind and solar power in China and other places worldwide.

IN "NILSSON A, LAZAREVIC D, B.N.: HOUSEHOLD RESPONSIVENESS TO RESIDENTIAL DEMAND RESPONSE STRATEGIES: RESULTS AND POLICY IMPLICATIONS FROM A SWEDISH FIELD STUDY. ENERGY POLICY 122 (2018) 273–286" To realize the benefits of smart grids, residential demand response (DR) aims to increase demand flexibility by influence household electricity consumption. Although price-based DR programs have shown potential, there is a need to further investigate the effectiveness of DR in energy strategy and policy development. The evaluation of DR has focused on the impact on overall power demand, assuming that consumers are economically rational decision-maker. However, recent findings suggest that consumer responses have been insufficient and calls have been made to identify novel evaluation approaches that better reflect the human dimension of energy consumption. Continuing this line of enquiry, this paper aims to investigate the effectiveness of DR and explore the potential of environmental incentives for increased consumer engagement. We propose an interdisciplinary evaluation framework to understand variations in household responsiveness to DR strategies, which is tested in a Swedish DR field trial covering 136 households during 2017. Results suggest that the effectiveness of DR varies widely across household type; ranging from substantial reductions in overall consumption and during peak periods, to increases in consumption during peak periods. Furthermore, a clear favor of price incentives, compared to environmental incentives, as the most efficient strategy to increase demand flexibility was observed.

EXISTING SYSTEM

In existing system, Support Vector Machines (SVM), decision tree classifier, random forest regression, and neural network [10]. Even though there are many algorithms to choose, only specific algorithms are suitable to make certain predictions. In this paper, a machine learning algorithm is applied to predict a met material Grid parameters,

DISADVANTAGES

- Doesn't Efficient for handling large volume of data.
- Theoretical Limits
- Incorrect Classification Results.
- Less Prediction Accuracy.

PROPOSED SYSTEM

The proposed model is introduced to overcome all the disadvantages that arises in the existing system. This system will increase the accuracy of the classification

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results by classifying the data based on the Smart Grid prediction dataset and others using CNN algorithms.It enhances the performance of the overall classification results.

ADVANTAGES

- High performance.
- Provide accurate prediction results.
- It avoid sparsity problems.
- Reduces the information Loss and the bias of the inference due to the multiple estimates.

MODULES

- Data Selection and Loading
- Data Preprocessing
- Splitting Dataset into Train and Test Data
- Classification
- Prediction
- Result Generation

MODULES DESCRIPTION

DATA SELECTION AND LOADING

- Data selection is the process of determining the appropriate data type and source, as well as suitable instruments to collect data.
- Data selection precedes the actual practice of data collection and it is the process where data relevant to the analysis is decided and retrieved from the data collection.

DATA PREPROCESSING

- The data can have many irrelevant and missing parts. To handle this part, data cleaning is done. It involves handling of missing data, noisy data etc.
- Missing Data:
  This situation arises when some data is missing in the data. It can be handled in various ways.
  - ✓ Ignore the tuples: This approach is suitable only when the dataset we have is quite large and multiple values are missing within a tuple.
  - ✓ Fill the Missing values: There are various ways to do this task. You can choose to fill the missing values manually, by attribute mean or the most probable value.
- Encoding Categorical data: That categorical data is defined as variables with a finite set of label

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values. That most machine learning algorithms require numerical input and output variables. That an integer and one hot encoding is used to convert categorical data to integer data.

- Count Vectorizer: Scikit-learn's CountVectorizer is used to convert a collection of text documents to a vector of term/token counts. It also enables the pre-processing of text data prior to generating the vector representation. This functionality makes it a highly flexible feature representation module for text.

SPLITTING DATASET INTO TRAIN AND TEST DATA

1. Data splitting is the act of partitioning available data into two portions, usually for cross-validator purposes.
2. One Portion of the data is used to develop a predictive model and the other to evaluate the model's performance.
3. Separating data into training and testing sets is an important part of evaluating data mining models.
4. Typically, when you separate a data set into a training set and testing set, most of the data is used for training, and a smaller portion of the data is used for testing.
5. To train any machine learning model irrespective what type of dataset is being used you have to split the dataset into training data and testing data.

CLASSIFICATION

Classification is the problem of identifying to which of a set of categories, a new observation belongs to, on the basis of a training set of data containing observations and whose categories membership is known.Random forests or random decision forests are an ensemble learning method for classification, regression and other tasks that operate by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes (classification) or mean/average prediction (regression) of the individual trees.

Decision Trees are a type of Supervised Machine Learning (that is you explain what the input is and what the corresponding output is in the training data) where the data is continuously split according to a certain parameter. An example of a decision tree can be explained using above binary tree The SVM is one of the most powerful methods in machine learning algorithms. It can find a balance between model complexity and classification ability

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given limited sample information. Compared to other machine learning methods, the SVM has many advantages in that it can overcome the effects of noise and work without any prior knowledge. The SVM is a non-probabilistic binary linear classifier that predicts an input to one of two classes for each given input. It optimizes the linear analysis and classification of hyperplane formation techniques. The NN algorithm is mainly used for classification and regression in machine learning. To determine the category of an unknown sample, all training samples are used as representative points, the distances between the unknown sample and all training sample points are calculated, and the NN is used. The category is the sole basis for determining the unknown sample category. Because the NN algorithm is particularly sensitive to noise data, the K-nearest neighbour algorithm (KNN) is introduced. The main concept of the KNN is that when the data and tags in the training set are known, the test data are input, the characteristics of the test data are compared with the features corresponding to the training set, and the most similar K in the training set is found.

PREDICTION

Predictive analytics algorithms try to achieve the lowest error possible by either using “boosting” or “bagging”.

Accuracy − Accuracy of classifier refers to the ability of classifier. It predict the class label correctly and the accuracy of the predictor refers to how well a given predictor can guess the value of predicted attribute for a new data.

Speed − Refers to the computational cost in generating and using the classifier or predictor.

Robustness − It refers to the ability of classifier or predictor to make correct predictions from given noisy data.

Scalability − Scalability refers to the ability to construct the classifier or predictor efficiently; given large amount of data.

Interpretability − It refers to what extent the classifier or predictor understands

CONCLUSION

Stability, reliability, security, efficiency and responsiveness of smart grid. The findings of the paper show that machine learning algorithms could be efficiently used for estimating transformer loss of life, detecting power quality events and faults, making optimal energy dispatch decisions to reduce cost of energy, efficient electricity market operations, and securing data and preventing attacks on smart grid. This paper has also discussed some of the challenges in implementing machine learning solutions for smart grid. These include limitation of finding past labelled data, evolution of new types of attacks, rapid changes in failure patterns, issues with generating high resolution synthetic data for training, finding efficient feature selection techniques, low memory and computational capability of smart meters. With the integration of new energy sources and technologies, smart grid is becoming increasingly complex and vulnerable. Although many machine learning based smart grid solutions have been proposed in the literature, there are still a lot of opportunities for improvement. Deep Learning and Big Data can play a vital role in solving problems of smart grid in future

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