Predicting Smart Grid Stability with Deep Learning

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Abstract— Smart grid is an advance concept of power system which harmonize electricity and communication in system network. It provides information for the producers, operator and the consumers on real time. There is an extreme demand to efficiently conduct this power supplied to the consumption domains such as household, organizations, industries, and smart cities. For this respect, a smart grid with stable systems is being expended to supply the dynamic power requirements. Predicting smart grid stability is still challenging. Many factors affect the stability of grid one of them is customer and producer participation. Identifying the participants may lead to the smart grid stabilities. In this work, we propose a deep learning model to detect the stability of the smart grid. The results of the proposed model are compared to other popular classifier models used in different studies like Support Vector Machine, Logistic Regression, Decision Tree, Random Forest, Gradient Boosted Trees, Multilayer neural network, Gated Recurrent Units, traditional LSTM and Recurrent Neural Networks and Multidirectional Long Short-Term Memory. The proposed model outperforms the other models with 98.35% accuracy.

I. Introduction

The role of IoT in smart grid is crucial. Internet of Things is in large part the enabler of smart grid as its technological and infrastructural components are largely IoT-based. IoT-based process automation Smart grid IoT technology is widely used to automate processes and increase efficiency in the supply chain. Producers and distributers: Adopt automated metering to monitor energy usage in real-time and dynamically respond to changing demand. Use environmental data and IoT technologies in renewable energy to optimize power production and maximize the use of green sources of energy. Monitor grid load and adopt data-driven strategy to minimize the risks of outages or overloads.

Predictive maintenance is one of the most important use cases for smart grid IoT applications for power plants, energy distributors and utilities. Operations on the upstream and downstream sides are built on the use of expensive equipment and infrastructure. Using intelligent grid technology for monitoring and energy grid management allows stakeholders to better control their assets, predict wear or malfunction and implement timely maintenance Real-time data analytics and visualization. As mentioned above, the role of big data in smart grid operation is very significant. Thanks to processing, sorting, cleaning, analysis and visualization of IoT data, stakeholders gain important insights about the processes in the supply chain from the moment the energy is produced to the point it is consumed by an end-user. Big data applications enable automation, management, problem detection and prediction in a smart energy grid. As explained in figure 1, smart grid requires reliability, maintainability, security, stability and few more to run efficiently.

Figure1: Requirements of Smart Grid

ADVANTAGES OF USING SMART GRIDS

As explained earlier, using smart grids provides a number of fascinating issues for managing, monitoring, controlling, securing and easier, faster and optimal. Here are the recommendations and important issues for smart grids summarized below as:

- Providing better power quality and quality of services
- Supporting distributed generation systems
- Enabling flexible system design
- Achieving easy operation and control
- Handling self-healing from power disturbance events
- Decreasing the defective effects of electrical chain on environment,
- Enabling active participation by consumers in demand response
- Operating resiliently against physical and cyber attack
- Enabling new products, services, and markets
- Optimizing assets and operations efficiently

The objective of this paper is to predict smart grid stability using given data.

Structure of the paper

The rest of the paper is structured as follows: section 2 proceeds with literature survey and findings. The methodology and its implementation are as presented in section 3, result outcomes are as shown in section 4. Finally, the conclusion and future works are followed in section 5.

II. Literature review

The grid denotes the electric grid which consists of communication lines, control stations, transformers, and distributors that aids in supplying power from the electrical plant to the consumers. Presently, the electric grid constitutes humongous power production units which generates millions of megawatts of power distributed across several demographic regions. There is a dire need to efficiently manage this power supplied to the various consumer domains such as industries, smart cities, household and organizations. In this regard, a smart grid with intelligent systems is being deployed to cater the dynamic power requirements. A smart grid system follows the Cyber-Physical Systems (CPS) model, in which Information Technology (IT) infrastructure is integrated with physical systems. In the scenario of the smart grid embedded with CPS, the Machine Learning (ML) module is the IT aspect and the power dissipation units are the physical entities. In this research, a novel Multidirectional Long Short-Term Memory (MLSTM) technique is being proposed to predict the stability of the smart grid network. The results obtained are evaluated against other popular Deep Learning approaches such as Gated Recurrent Units (GRU), traditional LSTM and Recurrent Neural Networks (RNN). The experimental results prove that the MLSTM approach outperforms the other ML approaches.

The advent of distributed and renewable energy sources, maintaining the stability of power grid is becoming increasingly difficult. Traditional power grid can be transformed into a smart grid by augmenting it with information and communication technologies, and machine intelligence. Machine learning and artificial intelligence can enable smart grid to make intelligent decisions and respond to sudden changes in customer demands, power outages, sudden drops and rises in renewable energy output or any other catastrophic events. Machine learning can also help capture customer consumption patterns, forecast energy demand and power generation of intermittent sources, and predict equipment failures. Reinforced learning can aid in making energy dispatch decisions and activate demand management signals in order to maintain balance of power supply and demand. The usage of wireless technologies in smart grid renders it vulnerable to cyber security threats. With the increase in data volume, it is now possible to employ machine learning for the detection and prevention of anomalous behaviour, intrusion, cyber-attacks, and malicious activities as well as data authentication. This paper reviews the application of different machine learning approaches that aims at enhancing the stability, reliability, security, efficiency and responsiveness of smart grid. This paper also discusses some of the challenges in implementing machine learning solutions for smart grid.

The current electric power system witnesses a significant transition into Smart Grids (SG) as a promising landscape for high grid reliability and efficient energy management. This ongoing transition undergoes rapid changes, requiring a plethora of advanced methodologies to process the big data generated by various units. In this context, SG stands tied very closely to Deep Learning (DL) as an emerging technology for creating a more decentralized and intelligent energy paradigm while integrating high intelligence in supervisory and operational decision-making. Motivated by the outstanding success of DL-based prediction methods, this article attempts to provide a thorough review from a broad perspective on the state-of-the-art advances of DL in SG systems. Firstly, a bibliometric analysis has been conducted to categorize this review's methodology. Further, we taxonomically delve into the mechanism behind some of the trending DL algorithms. We then showcase the DL enabling technologies in SG, such as federated learning, edge intelligence, and distributed computing. Finally, challenges and research frontiers are provided to serve as guidelines for future work in the futuristic power grid domain. This study's core objective is to foster the synergy between these two fields for decision-makers and researchers to accelerate DL's practical deployment for SG systems.

The infrastructure of the national grids of many countries is very old and includes classical technologies in terms of power production, transmission, and distributions. In addition, controllability and monitorability of these systems are also not satisfactory. On the other hand, smart grid technologies include sophisticated tools in order to monitor and control the power system in both ways from power stations to end-users or vice-versa. So that many vulnerabilities and power collapse can be detected in advance and necessary cautions can be taken. In addition, the smart grid system offers the monitoring and the management of the electrical energy from generation to end-user, and provides smart metering, vehicle to grid connection as well as integration of the renewable energy to the grid. Moreover, the efficient use of power sources with minimum loss and minimum illegal usage is also handled in smart grid technology. This paper highlights the effects of the smart grid technologies on the national grids and proposes some applicable suggestions to authorities in order to convert their classical grid system to the smart grid system.

The key work of smart grid equipment fault prediction and early warning, dynamic operation and maintenance strategy research is studied by using large data mining analysis method. Spark, Hive, HDFS（Hadoop Distributed File System）, MapReduce and other technologies are used to build a large data analysis and early warning decision-making platform for smart grid. In this paper, taking big data technology as the core, the BP neural network algorithm is optimized by using self-developed proprietary algorithm, which improves the accuracy of fault prediction model. The algorithm can realize the functions of intelligent inspection, intelligent research and judgment, intelligent early warning, intelligent decision-making and intelligent dispatch of substation equipment. Through a lot of practical verification, the accuracy of fault prediction of the platform is 93.98%, which is in the leading international level . In the field of smart grid, it has strong application value.

III. Methodology

The artificial neural network (ANN) architecture depicted below is the optimal one evaluated in this study. It reflects figure 2 with a sequential structure as explained below:

• one input layer (12 input nodes);

• Three hidden layers (24, 24 and 12 nodes, respectively);

• one single-node output layer.

As features are numerical real numbers within ranges, the choice of 'relu' as the activation function for hidden layers seems straightforward. Similarly, as this is a logistic classification exercise, where the output is binary ('0' for 'unstable', '1' for 'stable', following the map coding used in Section 4.3), the choice of 'sigmoid' as activation for the output layers seems obvious. Compilation with 'adam' as optimizer and 'binary_crossentropy' as the loss function follow the same logic. The fitting performance will be assessed using 'accuracy' as the metric of choice.

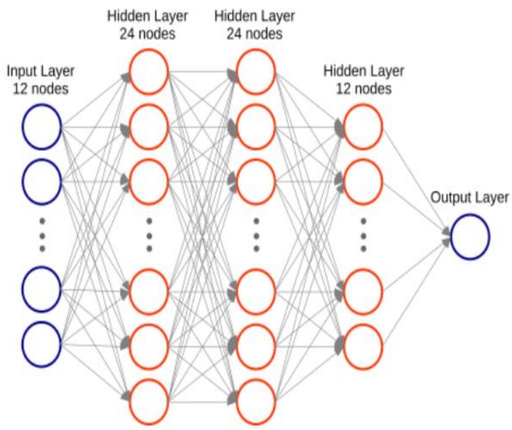

Figure2: artificial neural network (ANN) architecture

IV. Experimental results/snapshots

The final accuracy comes to 98.35% accuracy.

The architecture and the hyperparameters selected above led to the best prediction performance on the test set. In addition, several other combinations were evaluated for both the original dataset with 1,000 observations and the augmented dataset with 6,000 observations. It is important to emphasize that in this comparative assessment **no shuffling** of any type, at any part of the exercise, was performed, so that the very same testing set was exposed to model after fitting for performance assessment.

The table below summarizes obtained results:

Table 1: The original dataset with 1,000 observations

Original dataset (10,000 observations)					
Architecture	Folds	Epochs	Confusion Matrix		Accuracy
24-12-1	10	10	596	28	93.20%
			40	336	
24-12-1	10	20	605	19	95.00%
			31	345	
24-12-1	10	50	603	21	94.40%
			35	341	
24-24-12-1	10	10	604	20	95.00%
			30	346	
24-24-12-1	10	20	604	20	94.90%
			31	345	
24-24-12-1	10	50	602	22	95.80%
			20	356	

Table 1 describes accuracy of model when used on original dataset with no feature engineering. Table 2 describes accuracy of the model when the augmented data is applied.it performs better than on original dataset and state of art methods.

Table 2: The augmented dataset with 6,000 observations

Augmented dataset (60,000 observations)					
Architecture	Folds	Epochs	Confusion Matrix		Accuracy
24-12-1	10	10	3795	56	96.27%
			168	1981	
24-12-1	10	20	3780	71	97.50%
			79	2070	
24-12-1	10	50	3788	63	97.93%
			61	2088	
24-24-12-1	10	10	3778	73	97.20%
			95	2054	
24-24-12-1	10	20	3763	88	97.58%
			57	2092	
24-24-12-1	10	50	3797	54	97.98%
			67	2082	

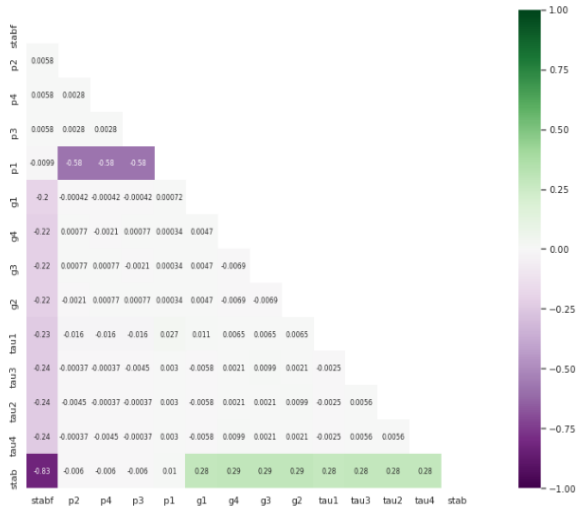

Figure3: overview of correlation between the dependent variable ('stabf') and the 12 numerical features.

Figure 3 shows correlation between the dependent variable ('stabf') and the 12 numerical features.

V. Conclusion and Future Work.

Deep learning proved to be an outstanding prediction tool for this particular application. Even considering that the dataset is well behaved and needed no significant pre-processing, the high accuracies obtained on the testing set confirm that a deep learning model may be safely considered. It would though be up to a smart grid operator to confirm if the accuracy level obtained with deep learning would suffice in practical terms (live network); As expected, more complex ANN architectures performed better than simpler ones; An increased number of epochs considered during fitting also plays a major role. It is evident that the more the model is exposed to the training set, the better the prediction accuracy; From a machine learning exercise perspective, the use of an augmented dataset with 6,000 observations contributed significantly to better results; It must be noted that input parameters utilized in the original DSGC simulations fall within predetermined ranges. As a follow-up step in the validation of this learning machine, it would be interesting to assess its performance using a new test set with observations obtained from simulations with input parameter values residing in other alternative ranges.

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