

## A Comprehensive Review of Artificial Neural Network Techniques Used for Smart Meter-Embedded forecasting System

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### ABSTRACT

The recent developments in computational science and smart metering have led to a gradual replacement of the traditional load forecasting methods by artificial intelligent (AI) technology. The smart meters for residential buildings have become available on the market, and since then, various studies on load forecasting have been published. Contingency planning, load shedding, management strategies and commercialization strategies are all influenced by load forecasts. Predicting a lower load than the actual load results in utilities not committing the necessary generation units and therefore incurring higher costs due to the use of peak power plants; on the other hand, predicting a higher load than actual will result in higher costs because unnecessary baseline units are stated and not used. Artificial Neural Networks (ANNs) provide an accurate approach to the problem of energy forecasting and have the advantage of not requiring the user to have a clear, understanding of the underlying mathematical relationship between input and output. The aim of this work is to carry-out Comprehensive Review of Artificial Neural Network Techniques Used for Smart Meter-Embedded forecasting System.

**Keywords:** Artificial Neural Network, Smart Meter, Artificial Intelligent, Energy, forecasting.

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### INTRODUCTION

The steady replacement of conventional or estimated meters by smart meters is a welcome technological enhancement. Historically we have measured energy consumption at the household level with analog or conventional meters installed at every consumer premises. The Characteristics of conventional meters and smart meters are stated as follows: Conventional electricity meters are ordinarily read only once per billing period. Smart meters on the other hand provide information on cost and amount of energy consumption in near real-time for both suppliers and consumers; Conventional electricity meters give no information as to when energy is consumed at each metered location.

However, Smart meters provide basic functions like automatic collection of electricity information, real-time monitoring of electricity load and inquiry. Furthermore, Smart meters offer numerous opportunities in electricity load analysis such as load prediction with high accuracy, intelligent management, and the smart distribution of power distribution system [1]. The Artificial Neural Network (ANN) has been a viable technique for energy forecasting. An accurate and efficient forecasting system helps the energy providers to plan ahead on the management of energy supply. It also helps the customers to maximize the utilization of smart prepaid meter. The

rest of this paper is organized as follows: Section I presents the concept of Smart meter, section II discusses on the concept of a forecasting system, section III reviews on the various

artificial neural network techniques used for smart meter-embedded forecasting system and section IV concludes the work.

### I. Concept of Smart Meter

The smart meters contain the meter board and the communication board connected through a serial port [2]. The meter board contains a set of tables storing various information including keys and passwords used for secure communication and privilege levels. It also performs power consumption measurements. The communication board is responsible for communications with the outside nodes such as collectors, other smart meters, or home appliances, and for performing any required computation [2]. Using an interrupt based mechanism; the communication board fetches data and other necessary information such as keys from the meter board whenever it needs to send data to the utility. Advanced Metering Infrastructure (AMI) also facilitates two-way communication [3] between meter and distribution system operator. The two-way communication enables several services for the distribution system operator that were difficult or impossible to implement without smart metering [2]. For example, power outage is detected faster by system operator and without interaction with the customer. Another service provided by smart metering is reporting the quality of power delivery (voltage, frequency) [2]. Smart metering also enables detailed monitoring of power flows within the distribution system that was previously available only at the substation level. Monitoring of power flows is important as it enables energy suppliers to react quickly on variations in Consumption levels [2]. The power flow monitoring information is also useful for real time pricing that is handled by one technology in smart grid known as Demand Side Management (DSM) [4]. If prices for energy are variable and react on current power flow information, real time pricing comes

into the picture. This is one feature of demand side management, where the energy supplier influences the consumption of energy directly and immediately [5]. The work carried out by [6] stated that the recent developments in digital intelligent smart meters have made it possible to monitor energy consumption in details never before seen. It proceeded by saying that the intelligent meters are part of a digitized society, which has been introduced over the last two decades, wherein home appliances, home automation and the smart meters make it possible to monitor energy consumption down to the second. The work further noted that historically we have measured energy consumption at the household level with analog meters installed at every consumer, and biannually the consumer has reported the meter reading to the utility company for billing purposes. Conversely, intelligent meters are directly connected to the utility company and are able to measure consumption autonomously down to seconds, made possible by the technological development and also pushed by legislation. The intelligent meters enable fast and accurate billing, and also offer a unique and unprecedented opportunity to log and analyse electricity consumption at the consumer level [6]. The high frequency electricity consumption data contain detailed information about consumption patterns, and this has initiated discussions among energy system stakeholders about utilizing the data for purposes other than billing. It has spawned diverse research projects; such as research on data security and anonymization, non-intrusive load monitoring, load forecasting and consumer classification [6].

### Smart Meter System

A smart metering system mainly consists of a smart meter, a collector/concentrator, communication network and a head-end data storage

system [7]. The smart meter consists of the metering module and a communication module with the Network interface card (NIC) [8]. Some smart

meters have a detachable communication module that can be easily plugged into the network module. This provides the advantage of using the metering module even if the communication technology is changed [8]. The communication network ideally requires a broad set of security

safeguards which may not be present in present advanced metering infrastructure (AMI) system. There are also online energy management systems but they are not yet advanced to the stage where consumer can modify their energy profile and meter setting [8].

## II. Concept of a forecasting System

Load forecasting is an integral part of electric power system operations, such as generation, transmission, distribution, and retail of electricity [9]. According to different forecast horizons and resolutions, load forecast problems can be grouped into 4 classes: long-term, mid-term, short-term and very short-term. The work in [10] noted that due to its fundamental role, Short-Term Load Forecasting (STLF) has been studied intensively over the past 50 years; however, the deployment of smart grid technologies brings new opportunities as well as challenges to the field. On a smart grid, load data can be collected at a much higher geographical granularity and frequency than before, by means of thousands of smart meters [11]. The work in [10] refers to a load time-series as "local" when it contains measurements relative to a small geographical region, whose average hourly load goes from several hundred up to several hundreds of thousands of kWh. It went further to state that despite the great variety of STLF methods proposed in the literature, most of them focus on load time-series relative to high aggregation levels (big towns, cities or entire countries), whose average goes from several to hundreds of MWh [12]. The work in [10] found out that these methods are not applicable to local STLF task for the following reasons : 1) Long training time: unlike for STLF focusing on high aggregation level, in local STLF we need to train and update thousands of models at the same time. It stated that predictions are made on hourly basis for many local regions, and the forecasting models must often be retrained (e.g., each month). An interesting work done by [13] stated that Load forecasts can be performed on different voltage levels in the grid. Forecasts can be performed on the transmission level, the distribution level

and even the individual household and device level, because with the introduction of smart meters, the load can now be measured on the household level [13]. The work further stated that the goal of their paper is to benchmark state-of-the-art methods for forecasting electricity demand on the household level across different granularities and time scales in an explorative way, thereby revealing potential shortcomings and find promising directions for future research in this area. It applied a number of forecasting methods including ARIMA, neural networks, and exponential smoothing using several strategies for training data selection, in particular day type and sliding window based strategies. It equally considered forecasting horizons ranging between 15 minutes and 24 hours. Its evaluation was based on two data sets containing the power usage of individual appliances at second time granularity collected over the course of several months. Its results indicated that forecasting accuracy varies significantly depending on the choice of forecasting methods/strategy and the parameter configuration. The work observed MAPEs in the range between 5 and >100%. And found out that the average MAPE for the first data set was ~30%, while it was ~85% for the other data set. It noted that these results showed big room for improvement. The work carried out by [14] noted that the forecast of electricity load is important for power system scheduling adopted by energy providers. It stated that inefficient storage and discharge of electricity could incur unnecessary costs, while even a small improvement in electricity load forecasting could reduce production costs and increase trading advantages, particularly during the peak electricity consumption periods.

### Categorisation of Load Forecasting

The load forecasting can be considered by the length of forecast interval. Although there is no official categorization in the power industry, there are four load forecasting types [9]: very short term load forecasting (VSTLF), short term load forecasting (STLF), medium term load forecasting (MTLF), and long term load forecasting (LTLF). The VSTLF typically predicts load for a period less than 24 h, STLF predicts load for a period greater than 24 h up to one week, MTLF forecasts load for a period from one week up to one year, and LTLF forecasts load performance for a period longer than one year [9]. The load forecasting type is chosen based on application requirements. Namely, VSTLF and STLF are applied to everyday power system operation and spot price calculation, so the accuracy requirement is much higher than for a long term prediction [9]. The MTLF and LTLF are used for prediction of power usage over a long

### III. Various Artificial Neural Network Techniques Used For Smart Meter-Embedded forecasting Systems

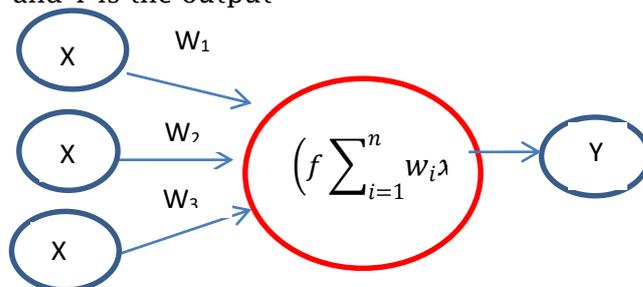
Artificial Neural Network (ANN) is an intelligent method in machine learning and cognitive neurosciences that is motivated by the functional aspect of the biological neural networks [21]. ANNs can be organized in different arrangements to implement a range of tasks including, data mining, classification, pattern recognition, forecasting, and process modelling [22]. It provides solutions where linear or nonlinear mapping of the model's input-target features are required, due to its learning ability, parallel processing, generalization, and the error tolerance [22]. The main advantage of neural network is that no clear relationship between the input variable and the output variable is required to be specified before the prediction process [22]. The work in [23] described the Neural Network architectures they used for electricity price estimation. The guiding equation of a neuron can be described as [23]:

$$y = f(\sum_i^{inputs} (w_i x_i + b_i))$$

The Equation 2.1 calculates the output of a neuron, where  $x$  is the input of the neuron,  $w$  is the weight on each connection to the neuron,  $b$  is the bias

period of time, and they are often referenced in long-term contracts when determining system capacity, costs of operation and system maintenance, and future grid expansion plans. Thus, if the smart grids are integrated with a high percentage of intermittent renewable energy, load forecasting will be more intense than that of traditional power generation sources due to the grid stability [15]. In addition, the load forecasting can be classified by calculation method into statistical methods and computational intelligence (CI) methods. With recent advances in computational science and smart metering, the existing load forecasting methods have been gradually replaced by AI technology. The smart meters for residential buildings have become available on the market around 2010, and since then, various studies on STLF for residential communities have been published [19–20].

and  $f$  is the activation function and the Rectified Linear Unit is the activation function in our experiments. The figure 1 is a simple representation of neural network where  $x_1$  to  $x_3$  are inputs of the neural network,  $w_1$  to  $w_3$  are the weights and  $Y$  is the output



**Figure 1: Simple Neural Network [23]**

The most popular neural network architecture is the Multi-Layer Perceptron (MLP) [24]. A typical MLP neural network has up to three layers. The first layer is called the input layer (the number of its nodes corresponds to the number of explanatory variables). The last layer is called the output layer (the number of its nodes corresponds to the number of response variables) [24]. An intermediary layer of nodes, the hidden layer, separates the input from the output layer [24]. Its number of

nodes defines the amount of complexity the model is capable of fitting. In addition, the input and hidden layer contain an extra node, called the bias node [24]. Normally, each node of one layer has connections to all the other nodes of the next layer and the network processes information as follows [24]: the input nodes contain the value of the descriptive variables. Since each node connection signifies a weight factor, the information reaches a single hidden layer node as the weighted sum of its inputs. Each node of the hidden layer passes the information through a nonlinear activation function and passes it on to the output layer if the calculated value is above a threshold [24]. It is crucial to stop the training procedure at the right time to prevent over fitting (this is called 'early stopping') [24]. This can be realized by allocating the dataset into 3 subsets respectively called the training and test sets used for simulating the data currently available

### 1) Modular Neural Networks

Modular Neural Networks have a collection of different networks working independently and contributing towards the output. Each neural network has a set of inputs which are unique compared to other networks constructing and performing sub-tasks [25]. The advantage of a modular neural network is that it breaks a large computational process into smaller

### 2) Convolutional Neural Networks (CNN)

The work carried out by [25] noted that Convolutional neural networks are similar to feed forward neural networks, where the neurons have learn-able weights and biases. Its application has been in signal and image processing which takes over Open source Computer Vision library (OpenCV) in field of computer vision. It stated that a Convolutional network (ConvNet) is applied in techniques like signal processing and image classification techniques. Also it noted that Computer vision techniques are dominated by convolutional neural networks because of their accuracy in image classification. The technique of image analysis and recognition, where the agriculture and weather features are extracted from the open source satellites like to predict the future growth and yield of a particular

to fit and tune the model and the validation set used for simulating future values. The network parameters are then estimated by fitting the training data using the above mentioned iterative procedure (back propagation of errors) [24]. The iteration length is optimised by maximising the forecasting accuracy for the test dataset and finally, the predictive value of the model is evaluated applying it to the validation dataset (out-of-sample dataset) [24]. The work in [25] stated that artificial neural networks are computational models which work similar to the functioning of a human nervous system. It noted that several kinds of artificial neural networks are implemented based on the mathematical operations and a set of parameters required determining the output. The following are the various Artificial Neural Network Techniques Used For Smart Meter-Embedded forecasting Systems

components decreasing the complexity [25]. This breakdown will help in decreasing the number of connections and negates the interaction of this network with each other, which in turn will increase the computation speed. However, the processing time will depend on the number of neurons and their involvement in computing the results [30].

land are being implemented [25]. CNNs have been used successfully in literature mainly for computer vision tasks such as image classification [26, 27]. CNNs use a specialized linear operation named convolution in at least one of the layers in the network. The work in [27] defined Convolutional neural networks as an operation on two functions on real valued arguments [27]. It further stated that convolution operation is denoted with an asterisk in equation 2.

$$S = x * w :2.$$

Where  $x$  denotes the input function,  $w$  denotes the weighting function. It also noted that in the context of CNNs, the weighting function is called a "kernel". The output of the convolution operation is often called the "feature map" (denoted by  $s$ ).

### 3) Nonlinear Autoregressive with Exogenous Inputs (Narx) Network

Artificial Neural Networks (ANNs) are used for an extensive range of issues as clustering, recognition, pattern classification, optimization, function approximation and prediction [28-29]. The NARX neural network is a good predictor of time series [30], [31]. NARX models can be used to model an extensive variety of nonlinear dynamic systems and they have been applied in various applications including time-series modelling. After the training phase, the NARX neural network is converted to the parallel architecture which is beneficial for multi-step-ahead prediction [32]. The writer in [33] mentioned that differently from other RNNs, the recurrence in the NARX network is given only by the feedback on the output, rather than from the whole internal state. The study carried out by [34] presented a novel implementation of a nonlinear autoregressive neural network with exogenous input (NARX). It noted that its approach showed that an ANN can be trained in open-loop by using all of the available endogenous and exogenous inputs. It stated that the network is a recursive ANN with connections between the output, hidden and input layers. It trained its network using a Levenberg-Marquardt back propagation algorithm. It further compared the proposed method with traditional statistical models ARMAX and state space, as well as the forecast calculated by a feed forward ANN with multilayer perceptron architecture. In all three cases, it indicated that the proposed NARX architecture provides a lower MAPE error. It highlighted that in practical terms, this translates into savings because the forecast load is used to commit power plants for power availability, and the more accurate the forecast is, the better the operations performance achieved, thus saving energy and cost. A NARX network can be implemented with a MultiLayer Perceptron (MLP). In order to evaluate the performance of forecasting models more accurately, the Mean Absolute Percentage Error (MAPE) and Cumulative Variation of Root Mean Square Error (CV-RMSE) can be employed [35]. The study by [36] presents an implementation of a

dynamic recurrent NARX ANN for load forecasting. It stated that the application is an electric substation, and the prediction forecast is for very short-term load forecasting (5 min) in order to feed an automatic generation control (AGC) in order to maintain the balance between the demand and supply of electricity. It used cross-validation in order to determine the structural parameters and the training of the NARX-neural network.

### 4) Long Short-Term Memory LSTM architecture

Long Short-Term Memory LSTM architecture has been used for energy forecasting. According to [33], Long Short-Term Memory (LSTM) architecture is widely used nowadays due to its superior performance in accurately modelling both short and long term dependencies in data. It noted that LSTM tries to solve the vanishing gradient problem by not imposing any bias towards recent observations, but it keeps constant error flowing back through time. The Long Short-Term Memory (LSTM) architecture was originally proposed by [34] and is widely used nowadays due to its superior performance in accurately modelling both short and long term dependencies in data. LSTM tries to solve the vanishing gradient problem by not imposing any bias towards recent observations, but it keeps constant error flowing back through time. LSTM works essentially in the same way as the ERNN architecture, with the difference that it implements a more elaborated internal processing unit called cell. LSTM has been employed in numerous sequence learning applications, especially in the field of natural language processing. Outstanding results with LSTM have been reached by [35] in unsegmented connected handwriting recognition [36] in automatic speech recognition, by [37] in music composition and by [38] in grammar learning. Further successful results have been achieved in the context of image tagging, where LSTM have been paired with convolutional neural network, to provide annotations on images automatically [39]. However, few works exist where LSTM has been

applied to prediction of real-valued time

#### 5) Gated Recurrent Unit (GRU)

Gated Recurrent Unit is one of the energy forecasting techniques. The work in [33] noted that the gated recurrent unit architecture is another important recurrent neural network. It indicated that in GRU, forget and input gates are combined into a single update gate, which adaptively controls how much each hidden unit can remember or forget. It stated that the internal state in GRU is always fully exposed in output, due to the lack of a control mechanism, like the output gate in LSTM. The (GRU) is another notorious gated architecture, originally proposed by [40], which adaptively captures dependencies at different time scales. In GRU, forget and input gates are combined into a single update gate, which adaptively controls how much each hidden unit can remember or forget. The internal state in GRU is always fully exposed in output, due to the lack of a control mechanism, like the output gate in LSTM. GRU were firstly tested by [40] on a statistical machine translation task

#### 6) Echo State Neural Network (ESN)

The Echo state neural network consists of a large, sparsely connected, untrained recurrent layer of nonlinear units and a linear, memory-less read-out layer, which is trained according to the task that the ESN is demanded to solve [42]. The work in [43] stated that the Echo State Network has been largely employed in STLF and equally it is not implemented as a BPPT. ESNs are characterized by a very fast learning procedure, which usually consists in solving a convex optimization problem [44]. ESNs, along with Liquid State Machines [43], belong to the class of computational dynamical systems implemented according to the so-called reservoir computing framework [45]. ESN have been applied in a variety of different contexts, such as static classification [50], speech recognition [46], intrusion detection [51], adaptive control [52], detrending of non-stationary time series [53], harmonic distortion measurements [54] and, in general, for modelling of various kinds of non-linear dynamical systems [55]. ESNs have been extensively employed to forecast real valued time series. The

series.

and reported mixed results. In an empirical comparison of GRU and LSTM, configured with the same amount of parameters, The work done by [41] concluded that on some datasets GRU can outperform LSTM, both in terms of generalization capabilities and in terms of time required to reach convergence and to update parameters. In an extended experimental evaluation, the work by [42] employed GRU to (i) compute the digits of the sum or difference of two input numbers (ii) predict the next character in a synthetic XML dataset and in the large words dataset Penn TreeBank, (iii) predict polyphonic music. The results showed that the GRU outperformed the LSTM on nearly all tasks except language modelling when using a naive initialization. However according to the work done by [30] there are no researches where the standard GRU architecture has been applied in STLF problems.

work done by [56] trained an ESN to perform multivariate time series prediction by applying a Bayesian regularization technique to the reservoir and by pruning redundant connections from the reservoir to avoid overfitting. Superior prediction capabilities have been achieved by projecting the high-dimensional output of the ESN recurrent layer into a suitable subspace of reduced dimension [57]. An important context of application with real valued time series is the prediction of telephonic or electricity load, usually performed 1-hour and a 24-hours ahead [58]. Important results have been achieved in the prediction of chaotic time series by [59]. They proposed an alternative to the Bayesian regression for estimating the regularization parameter and a Laplacian likelihood function, more robust to noise and outliers than a Gaussian likelihood. The author in [60, 61, 62, 63] applied an ESN-based predictor on both benchmark and real dataset, highlighting the capability of these networks to learn amazingly accurate models to forecast a chaotic process from almost noise-free

training data [64,65,66]. An ESN consists of a large, sparsely connected, untrained recurrent layer of nonlinear units and a

linear, memory-less read-out layer, which is trained according to the task that the ESN is demanded to solve[67].

### 7) Elman Recurrent Neural Network (ERNN)

Elman Recurrent Neural Network (ERNN) has been applied in many different contexts. The Elman Recurrent Neural Network (ERNN), also known as Simple RNN or Vanillan RNN, ERNN demonstrated to be capable of learning grammar using a training set of unannotated sentences to predict successive words in the sentence [68] The work done by [69] studied ERNN performance in short-term load forecasting and proposed a learning method called “diffusion learning” (a sort of momentum-based gradient descent), to avoid local minima during the optimization procedure. Also the work done by [70] trained ERNN with a hybrid algorithm that combines particle swarm optimization and evolutionary computation to overcome the local minima issues of gradient-based methods. Furthermore, ERNNs have been employed by [60,71, 72] in tourist arrival forecasting and by [61, 73] to predict electric load time series. Due to the critical dependence of electric power usage on the day of the week or month

of the year, a pre-processing step is performed to cluster similar days according to their load profile characteristics. The work by [62,74,75] proposes a variant of ERNN called Self-Recurrent Wavelet Neural Network, where the ordinary nonlinear activation functions of the hidden layer are replaced with wavelet functions. This leads to a sparser representation of the load profile, which demonstrated to be helpful for tackling the forecast task through smaller and more easily trainable networks.

In [63,64,65,66,67,68,71,74,75] a detailed and comprehensive work on solar optimization and fabrication was done which also enhances steady power supply. These recent papers by different authors comprehensively reviewed different optimizations techniques of power efficiency enhancement techniques such as Maximum power point tracking (MPPT) of solar photovoltaic panels and other renewable energy enhancement and optimization methods.

### CONCLUSION

This work presents a Comprehensive Review of Artificial Neural Network Techniques Used For Smart Meter-Embedded forecasting System. The growing number of Electric consumers and inadequate information on the operation of the smart meter energy system has caused a strain on the management of energy distribution and consumption. A balance is therefore required by maximising the utilization of smart meter energy system by developing an affordable accurate and trustworthy data for billing Electric customer. Energy forecasting accuracy varies significantly depending on the

choice of forecasting methods/strategy and the parameter configuration. Artificial neural networks have a very been widely used for energy forecasting. The forecast of electricity load is important for power system scheduling adopted by energy providers. Inefficient storage and discharge of electricity could incur unnecessary costs, while even a small improvement in electricity load forecasting could reduce production costs and increase trading advantages, particularly during the peak electricity consumption periods.

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### REFERENCES

- [1] Woon et al. (Eds.), Neural Networks, Springer International Publishing AG 2017 W.L. DARE 2016, LNAI 10097, pp. 10-21, 2017.

- [2] Amrita G; & Mauro C, Key Management Systems for Smart Grid Advanced Metering Infrastructure: A Survey, 2018
- [3] Mohassel R. R., Fung A., Mohammadi F., and Raahemifar K., "A survey on advanced metering infrastructure," *International Journal of Electrical Power & Energy Systems*, vol. 63, pp. 473-484, 2014.
- [4] Kabalci Y., "A survey on smart metering and smart grid communication," *Renewable and Sustainable Energy Reviews*, vol. 57, pp. 302-318, 2016.
- [5] Finster S. and Baumgart I., "Privacy-aware smart metering: A survey," *IEEE Communications Surveys & Tutorials*, vol. 16, no. 3, pp. 1732-1745, 2014.
- [6] Alexander M T, Per S N, Structured Literature Review of Electricity Consumption Classification Using Smart Meter Data, 2017.
- [7] Zafar, N, et al. "System security requirements analysis: a smart grid case study." *System engineering* 2013
- [8] Rani Y, Roger C, "Architecture and Data flow model for consumer-oriented smart meter Design", 23rd international conference on information Development, available at <http://www.rogerclarke.com/Ec/s-m-ADF.html>, 2014.
- [9] Ekonomou, L.; Christodoulou, C.A.; Mladenov, V. A short-term load forecasting method using artificial neural networks and wavelet analysis. *Int. J. Power Syst.* 1, 64-68, 2016.
- [10] The-Hien Dang-Ha, Filippo Maria Bianchi, Roland Olsson, Local Short Term Electricity Load Forecasting: Automatic Approaches, 2017
- [11] Tao Hong and Mohammad Shahidehpour. Load Forecasting Case Study. National Association of Regulatory Commissioners, pages 1-171, 2015
- [12] Yannig Goude, Raphael Nedellec, and Nicolas Kong. Local short and middle term electricity load forecasting with semi-parametric additive models. *IEEE Transactions on Smart Grid*, 5(1):440-446, 2014.
- [13] Andreas V, Christoph G, Rohit T, Christoph D and Hans A J, Household Electricity Demand Forecasting - Benchmarking State-of-the-Art Methods, 2014.
- [14] Cho, H.; Goude, Y.; Brossat, X.; Yao, Q. Modeling and forecasting daily electricity load curves: A hybrid approach. *J. Am. Stat. Assoc.* 108, 7-21, 2013.
- [15] Ping h k, and Chiou J h , A High Precision Artificial Neural Networks Model for Short-Term Energy Load Forecasting, 2018
- [16] Valgaev, O, Kupzog, F. Low-Voltage Power Demand Forecasting Using K-Nearest Neighbors Approach. In *Proceedings of the Innovative Smart Grid Technologies—Asia (ISGT-Asia)*, Melbourne, VIC, Australia, 28 November-1 December 2016.
- [17] Valgaev, O.; Kupzog, F. Building Power Demand Forecasting Using K-Nearest Neighbors Model—Initial Approach. In *Proceedings of the IEEE PES Asia-Pacific Power Energy Conference*, Xi'an, China, pp. 1055-1060. 2016.
- [18] Chen, C.P.; Zhang, C.-Y. Data-intensive applications, challenges, techniques and technologies: A survey on Big Data. *Inf. Sci.* 2014, 275, 314-347.
- [19] Fallah S N, Deo R C , Shojafer M , Conti M and Shamshirband S, Computational Intelligence Approaches for Energy Load Forecasting in Smart Energy Management Grids: State of the Art, Future Challenges, and Research Directions, 2018
- [20] Ugurlu U, Oksuz I, Tas O, Article Electricity Price Forecasting Using Recurrent Neural Networks 2018.
- [21] Sermpinis, G., Laws, J., and Dunis, C.L., "Modelling commodity value at risk with Psi Sigma neural networks using open-high-low-close data", *European Journal of Finance*, 21(4), pp. 316-336. 2014
- [22] Kishan M, 6 Types of Artificial Neural Networks Currently Being Used in Machine Learning, 2018
- [23] ] LeCun Y., Bengio Y., and G.. "Deep learning." *Nature* 521.7553 (2015): 436-444. 2015
- [24] Bengio Y., Goodfellow I. J., and Courville A.. "Deep learning." An MIT Press book in preparation. Draft

- chapters available at <http://www.iro.umontreal.ca/~bengioy/dlbook> (2015).
- [25] Araújo, R.A.; Oliveira, A.L.I.; Meira, S. A morphological neural network for binary classification problems. *Eng. Appl. Artif. Intell.* 2017, 65, 12–28.
- [26] Gong, T.; Fan, T.; Guo, J.; Cai, Z. GPU-based parallel optimization of immune convolutional neural network and embedded system. *Eng. Appl. Artif. Intell.* 2017, 62, 384–395.
- [27] Mohanty, S.; Patra, P.K.; Sahoo, S.S. Prediction of global solar radiation using nonlinear autoregressive network with exogenous inputs (narx). In *Proceedings of the 39th National System Conference (NSC)*, Noida, India, 14–16 December 2015.
- [28] Ruiz, L.G.B.; Cuéllar, M.P.; Calva-Flores, M.D.; Jiménez, M.D.C.P. An Application of Non-Linear Autoregressive Neural Networks to Predict Energy Consumption in Public Buildings. *Energies* 2016, 9, 684. [CrossRef]
- [29] Cadenas, E.; Rivera, W.; Campos-Amezcu, R.; Heard, C. Wind Speed Prediction Using a Univariate ARIMA Model and a Multivariate NARX Model. *Energies* 2016, 9, 109.
- [30] Filippo M B, Enrico M, Michael C K, Antonello R and Robert J, An overview and comparative analysis of recurrent neural networks for short term load forecasting, 2017.
- [31] Jaime B , Shihab A, Short-Term Forecasting of Electric Loads Using Nonlinear Autoregressive Artificial Neural Networks with Exogenous Vector Inputs, 2017
- [32] Ping H K, Chiou-J H, A High Precision Artificial Neural Networks Model for Short-Term Energy Load Forecasting, *Energies* 2018, 11, 213
- [33] De Andrade, L.C.M.; Oleskovicz, M.; Santos, A.Q.; Coury, D.V.; Fernandes, R.A.S. Very short-term load forecasting based on NARX recurrent neural networks. In *Proceedings of the IEEE PES General Meeting Conference and Exposition*, National Harbor, MD, USA, pp.1–5. 2014.
- [34] S. Hochreiter, J. Schmidhuber, Long short-term memory, *Neural computation* 9 (8) (1997) 1735–1780
- [35] A. Graves, J. Schmidhuber, Offline handwriting recognition with multidimensional recurrent neural networks, in: *Advances in neural information processing systems*, 545–552, 2009.
- [36] A. Graves, A.-r. Mohamed, G. Hinton, Speech recognition with deep recurrent neural networks, in: *Acoustics, Speech and Signal Processing (ICASSP)*, 2013 IEEE International Conference on, IEEE, 6645–6649, 2013.
- [37] D. Eck, J. Schmidhuber, Finding temporal structure in music: Blues improvisation with LSTM recurrent networks, in: *Neural Networks for Signal Processing*, 2002. *Proceedings of the 2002 12th IEEE Workshop on*, IEEE, 747–756, 2002.
- [38] F. A. Gers, J. Schmidhuber, LSTM recurrent networks learn simple context-free and context-sensitive languages, *Neural Networks, IEEE Transactions on* 12 (6) (2001) 1333–1340.
- [39] O. Vinyals, A. Toshev, S. Bengio, D. Erhan, Show and Tell: Lessons Learned from the 2015 MSCOCO Image Captioning Challenge, *IEEE Trans. Pattern Anal. Mach. Intell.* 39 (4) (2017) 652–663.
- [40] K. Cho, B. Van Merriënboer, C. Gulcehre, D. Bahdanau, F. Bougares, H. Schwenk, Y. Bengio, Learning phrase representations using RNN encoder-decoder for statistical machine translation, *arXiv preprint arXiv:1406.1078*.
- [41] J. Chung, C. Gulcehre, K. Cho, Y. Bengio, Empirical Evaluation of Gated Recurrent Neural Networks on Sequence Modeling, *CoRR abs/1412.3555*.
- [42] W. Zaremba, An empirical exploration of recurrent network architectures, *Proceedings of the 32nd International Conference on Machine Learning*, Lille, France .
- [43] W. Maass, T. Natschläger, H. Markram, Real-time computing without stable states: A new framework for neural computation based on perturbations, *Neural computation* 14 (11) (2002) 2531–

- 2560, DOI: 10.1162/089976602760407955.
- [44] W. Maass, T. Natschläger, H. Markram, Real-time computing without stable states: A new framework for neural computation based on perturbations, *Neural computation* 14 (11) (2002) 2531-2560, DOI: 10.1162/089976602760407955.
- [45] L. A. Alexandre, M. J. Embrechts, J. Linton, Benchmarking reservoir computing on time-independent classification tasks, in: *Neural Networks, 2009. IJCNN 2009. International Joint Conference on, IEEE*, 89-93, 2009.
- [46] M. D. Skowronski, J. G. Harris, Automatic speech recognition using a predictive echo state network classifier, *Neural networks* 20 (3) (2007) 414-423.
- [47] D. Hai-yan, P. Wen-jiang, H. Zhen-ya, A multiple objective optimization-based echo state network tree and application to intrusion detection, in: *VLSI Design and Video Technology, 2005. Proceedings of 2005 IEEE International Workshop on*, 443-446, DOI: 10.1109/IWVDVT.2005.1504645, 2005.
- [48] S. Han, J. Lee, Fuzzy Echo State Neural Networks and Funnel Dynamic Surface Control for Prescribed Performance of a Nonlinear Dynamic System, *Industrial Electronics, IEEE Transactions on* 61 (2) (2014) 1099-1112, ISSN 0278-0046, DOI: 10.1109/TIE.2013.2253072.
- [49] E. Maiorino, F. Bianchi, L. Livi, A. Rizzi, A. Sadeghian, Data-driven detrending of nonstationary fractal time series with echo state networks, *Information Sciences* 382-383 (2017) 359-373, DOI: 10.1016/j.ins.2016.12.015.
- [50] J. Mazumdar, R. Harley, Utilization of Echo State Networks for Differentiating Source and Nonlinear Load Harmonics in the Utility Network, *Power Electronics, IEEE Transactions on* 23 (6) (2008) 2738-2745, ISSN 0885-8993, DOI: 10.1109/TPEL.2008.2005097.
- Ogbonna *et al*
- [51] S. I. Han, J. M. Lee, Fuzzy echo state neural networks and funnel dynamic surface control for prescribed performance of a nonlinear dynamic system, *Industrial Electronics, IEEE Transactions on* 61 (2) (2014) 1099-1112.
- [52] D. Niu, L. Ji, M. Xing, J. Wang, Multi-variable Echo State Network Optimized by Bayesian Regulation for Daily Peak Load Forecasting, *Journal of Networks* 7 (11) (2012) 1790-1795. [
- [53] S. Løkse, F. M. Bianchi, R. Jenssen, Training Echo State Networks with Regularization Through Dimensionality Reduction, *Cognitive Computation* (2017) 1-15 ISSN 1866-9964, DOI: 10.1007/s12559-017-9450-z.
- [54] S. Varshney, T. Verma, Half Hourly Electricity Load Prediction using Echo State Network, *International Journal of Science and Research* 3 (6) (2014) 885-888.
- [55] D. Li, M. Han, J. Wang, Chaotic time series prediction based on a novel robust echo state network, *IEEE Transactions on Neural Networks and Learning Systems* 23 (5) (2012) 787-799.
- [56] H. Jaeger, H. Haas, Harnessing Nonlinearity: Predicting Chaotic Systems and Saving Energy in Wireless Communication, *Science* 304 (5667) (2004) 78-80, ISSN 0036-8075, DOI:10.1126/science.1091277.
- [57] J. L. Elman, Language as a dynamical system, *Mind as motion: Explorations in the dynamics of cognition* (1995) 195-223.
- [58] H. M. H. Mori, T. O. T. Ogasawara, A recurrent neural network for short-term load forecasting, 1993 *Proceedings of the Second International Forum on Applications of Neural Networks to Power Systems* 31 (1993) 276-281, DOI: 10.1109/ANN.1993.264315
- [59] X. Cai, N. Zhang, G. K. Venayagamoorthy, D. C. Wunsch, Time series prediction with recurrent neural networks trained by a hybrid PSO-EA algorithm, *Neurocomputing* 70 (13-15) (2007) 2342-2353, ISSN 09252312, DOI: 10.1016/j.neucom.2005.12.138.

- [60] V. Cho, A comparison of three different approaches to tourist arrival forecasting, *Tourism Management* 24 (3) (2003) 323 - 330, ISSN 0261-5177, DOI: [http://doi.org/10.1016/S0261-5177\(02\)00068-7](http://doi.org/10.1016/S0261-5177(02)00068-7).
- [61] P. Mandal, T. Senjyu, N. Urasaki, T. Funabashi, A neural network based several-hour-ahead electric load forecasting using similar days approach, *International Journal of Electrical Power and Energy Systems* 28 (6) (2006) 367-373, ISSN 01420615, DOI: 10.1016/j.ijepes.2005.12.007.
- [62] H. Chitsaz, H. Shaker, H. Zareipour, D. Wood, N. Amjady, Short-term electricity load forecasting of buildings in micro-grids, *Energy and Buildings* 99 (2015) 50-60, ISSN 03787788, DOI: 10.1016/j.enbuild.2015.04.011.
- [63] V. H. U. Eze, O. N. Iloanus, M. C. Eze, and C. C. Osuagwu, "Maximum power point tracking technique based on optimized adaptive differential conductance," *Cogent Eng.*, vol. 4, no. 1, pp. 1-13, 2017, doi: 10.1080/23311916.2017.1339336.
- [64] V. S. Enyi, V. H. U. Eze, F. C. Ugwu, and C. C. Ogbonna, "Path Loss Model Predictions for Different Gsm Networks in the University of Nigeria , Nsukka Campus Environment for Estimation of Propagation Loss," *Int. J. Adv. Res. Comput. Commun. Eng.*, vol. 10, no. 8, pp. 108-115, 2021, doi: 10.17148/IJARCC.2021.10816
- [65] M. C. Eze, V.H.U Eze *et al.*, "Solar Energy Materials and Solar Cells Optimum silver contact sputtering parameters for efficient perovskite solar cell fabrication," *Sol. Energy Mater. Sol. Cells*, vol. 230, no. November 2020, p. 111185, 2021,doi:10.1016/j.solmat.2021.111185.
- [66] V. H. U. Eze, U. O. Oparaku, A. S. Ugwu, and C. C. Ogbonna (2021): "A Comprehensive Review on Recent Maximum Power Point Tracking of a Solar Photovoltaic Systems using Intelligent , Non-Intelligent and Hybrid based Techniques," *Int. J. Innov. Sci. Res. Technol.*, 6(5):456-474.
- [67] V. H. U. Eze, M. C. Eze, C. C. Ogbonna, S. A. Ugwu, K. Emeka, and C. A. Onyeke (2021).Comprehensive Review of Recent Electric Vehicle Charging Stations, *Glob. J. Sci. Res. Publ.*, 1(12):16-23.
- [68] V. H. U. Eze, M. C. Eze, V. Chijindu, E. Chidinma E, U. A. Samuel, and O. C. Chibuzo (2022) Development of Improved Maximum Power Point Tracking Algorithm Based on Balancing Particle Swarm Optimization for Renewable Energy Generation," *IDOSR Journal of Applied Sciences*, 7(1):12-28.
- [69] William Mufana Masisani, Ibrahim Adabara (2022). Monitoring with Communication Technologies of the Smart Grid. *IDOSR Journal of Applied Sciences*,7(1): 102-112.
- [70] Patience Nabiryo, Anthony Ekeh Itodo (2022). Design and Implementation of Base Station Temperature Monitoring System Using Raspberry Pi. *IDOSR Journal of Science and Technology*,7(1): 53-66.
- [71] WM Masisani and I Adabara (2022). Implementation of Smart Grid Decision Support Systems. *IDOSR Journal of Scientific Research*, 7 (1), 50-57.
- [72] A Natumanya (2022). Design and Construction of an Automatic Load Monitoring System on a Transformer in Power Distribution Networks. *IDOSR Journal of Scientific Research* 7 (1), 58-76.
- [73] WM Masisani, I Adabara (2022).Overview of Smart Grid: A Review. *IDOSR Journal of Computer and Applied Sciences* 7 (1), 33-44.
- [74] M Kalulu (2022). The Smart Grid and Its Security Challenges. *INOSR Applied Sciences* 9 (1), 9-12.
- [75] K Joel, E Anthony (2022). RF Based Remote Driver's Condition Monitoring System Using Atmega328p *INOSR Applied Sciences* 9 (1), 13-25.