An Investigation into the Methods and Applications of Deep Learning in Smart Grid

Rituraj Rituraj

June 19, 2022

An Investigation into the Methods and Applications of Deep Learning in Smart Grid

Rituraj Rituraj
Doctoral School of Applied Informatics and Applied Mathematics
Obuda University
Budapest, Hungary
rituraj88@stud.uni-obuda.hu

Abstract— **The manuscript represents the state-of-the-art review of the deep learning methods for smart grid applications. This paper reviews novel applications of deep learning algorithms in smart grid. The deep learning based three algorithms i.e., Long-Short Term Memory, recurrent neural network, convolution neural network found to be most useful in smart grid application. These algorithms are found to be most useful for forecasting, cyber-attack, anomaly detection and electricity theft in smart grid. This paper briefly surveys the most usable deep learning algorithms for making the smart is resilience, accurate, and safe. The review result shows that the mentioned deep learning algorithms give an excellent results over other deep learning algorithm. Therefore, these three algorithms are widely acceptable for the evaluation of smart grids.**

Keywords—Smart Grid, Deep Learning, Long-Short Term Memory, Recurrent Neural Network, Convolution Neural Network.

I. Introduction

Deep learning (DL), which is based on artificial neural networks (ANN) with representation learning, has recently resurrected machine learning [1]. Because of its capabilities, different types of DL approaches are accessible in the literature, each with its own set of applications [2]. ML and DL aids in the analysis of smart grid applications in terms of efficiency and efficacy [3] . To safeguard the smart grid (SG) from cyber threats, such as collectively designing and creating appropriate SG testbeds to promote research [4]. A deep neural network is in fact an autoencoder for presenting relatively a set of data with degraded dimension [5]. Through the demand side management (DSM) system, the home energy management system efficiently schedules the appliances to achieve peak-average ration minimization, energy savings, and cost reduction [6]. To achieve the ideal set-point of smart inverters and the arrangement of capacitor banks for accomplishing dual timeframe voltage control in distribution networks, several researchers used an alternating current power flow model using deep Q networks [7].

Adversarial attacks are inherently covert and capable of causing random or targeted malicious effects by substituting artificial adversarial instances for natural inputs in a target model [8]. False data injection attack detection (FDIA) scheme based on the Kalman filter and recurrent neural network can be used for state prediction [9]. The computational cost of DL results in an unavoidable disconnect between theoretical analysis and real-time actions [10]. A graphical model-based method for detecting abnormalities in SG control systems uses Bayesian networks to map the interaction between sensors and actuators [11]. DL provides particular benefits in handling complicated issues like power system frequency analysis and control [12]. The existing ML-based FDIA detection algorithms change measured data to malicious measurement data with false data injection attacks [13]. The significance of electricity theft detection in SG is crucial for cost-effectiveness [14].

The application of DL in SG makes the power system secure and cost-effective. Even after such a great advantage of DL, it seems that SGs still have to help the power companies to enhance their operating and environmental performance. In addition, there is a research gap for the implication of DL in electric vehicles. To achieve a clean environment, electric vehicles will play an important role. If the DL concept applies in this sector, it would certainly transform the SG and helps to protect the environment. This motivates the author to do this literature review on the application of DL in SG.

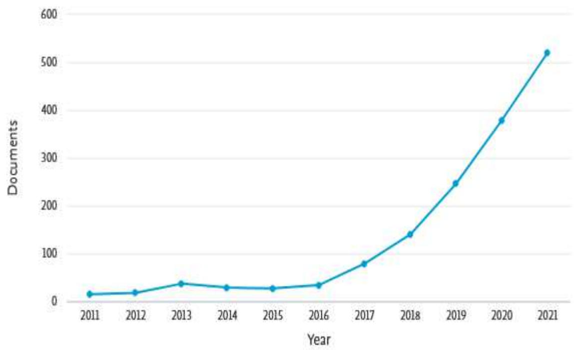

Fig. 1 A decade of deep learning in smart grid

The progress of a decade of deep learning in smart grid is represented in Fig 1. The figure shows that between 2011to 2016, the pace of research on DL was very slow but after 2017 there are high increases in this field. The new algorithm of DL gives good results in making the traditional power system into a smart power system.

II. Materials and Methods

The WOS has been explored from the year 2011 to 2022. The inquiries include a combination of all the deep learning methods with "smart grid". The search resulted in 1750 articles. Among them 200 had been selected as the most relevant through screening the titles and the abstracts of the manuscripts. In the second step, the classification of the method based on the deep learning method had been performed along with the PRISMA. The method of state-of-the-art review had been adapted from [15-27]. After in dept study of the refined articles. The fundamental and novel methods of the deep learning had been identified and classified in the table 1. Further tables had been constructed based on the method of deep learning.

III. State of the Art

The fundamental and novel methods of the deep learning had been identified and classified in the table 1.

Table I. Notable deep learning methods and their applications in smart grid

References	Year	Source	Application	Methods/Algorithms
{28]	2022	Computers and Electrical Engineering	Risk management and cyberattacks detections	SVM, and DNN
[29]	2022	Electrical Engineering	Real-time exact data intrusion detection	State estimation, K-nearest neighbors, SCADA.
[30]	2022	Intelligent Engineering and Systems	Model and validate a secure home area network	Deep auto-encoders; Honeypot algorithm;
[31]	2021	Computers and Electrical Engineering	False data cyber data	DNN, Agent-based model
[32]	2021	Energy Research	Forecasting residential energy management	Pooling-based deep neural network, Neural network auto aggressive integral moving average
[33]	2021	Soft Computing	Damage in the transmission lines	Convolution neural network (CNN), SVM
[34]	2021	IEEE Access	Effective pricing schemes	Reinforcement learning
[35]	2021	IEEE Access	Analyse accuracy, limitations	Federated learning, Edge intelligence, and Distributed computing.
[36]	2020	IEEE Internet of Things Journal	Market frequency efficiency	DNN, Security-constrained economic dispatch model, Stacked denoising autoencoders
[37]	2020	Electrical Power and Energy Systems	Technical losses in large-scale SG	Clustering algorithm, DNN loss model,
[38]	2020	Electrical Energy Systems	Electricity Theft	SVM, RF, 1D-CNN
[39]	2020	IEEE Industrial Informatics	Uncertainty of customer's groups	Bayesian deep learning; Clustering-based pooling
[40]	2020	Energies	Energy consumption forecasting	Factored conditional restricted Boltzmann machine forecasting module, Genetic Algorithm, Evolution algorithm, ANN
[41]	2020	Energy	Real-time economic generation dispatch	Expandable deep learning algorithms, Imperialist competitive algorithm, Shuffled frog leaping algorithm
[42]	2020	IEEE Access	Short-term load forecasting	Deep neural network and Iterative ResBlock

SG is very vulnerable to cyber-attacks. This is because it is a combination of communication systems and the Internet of Things (IoT). DT and DNN classifiers can be used for constructing a unique symmetric demonstration of the asymmetric datasets of the SG control systems. This incorporates detecting attacks in SG [28].. The DL-based model in combination with the classical bad data detection algorithms can detect unstructured and structured false data inoculation attacks [29]. The SG systems manage the operation of all associated components due to the integrated communication infrastructures. The Trust-Based Iterative Energy-Efficient Routing Protocol can help in secured data transmission in the home area network [30]. An agent-based approach provides attack exposure matrices with the integration of true data. The agent-based approach also helps in the decentralization of the data integrity system [31]. The DL algorithm can also help forecast computer-aided residential energy management [32]. The DL algorithms, like CNN and SVM, can be used to identify the damages in the transmission lines [33].

The demand response modeling using the DL algorithms like robust adversarial reinforcement learning and gradient-based Nikaido-Isoda function provides an optimal strategy that exhibits the analysis of scheduling of appliances [34]. The DL has several applications in the SG paradigm. It can help to analyze the extent of limitations, awareness, prediction, feasible scenarios, accuracy, and many more [35].

In SGs, we can maximize the social welfare can be maximized by making a balance between power supply and demand through the electricity market. The increasing frequency of SG requires fast tuning strategy of neural networks to significantly handle the topology change [36]. The DL algorithms such as clustering can formulate power loss estimators for large-scale low-voltage distribution areas. These areas can be uncertainty in the smart meters, load unbalances, and power variability from distributed generation [37] . DL can be useful in the classification of non-periodicity of electricity that helps in identifying the power theft by the consumer [38]. The clustering-based pooling method can address the overfitting data gathered from the smart meters by increasing the data diversity and volume for the framework which improves the predictive performances [39]. DL-based modules improve authenticity with reasonable convergence of the predicted results [40]. DL algorithms are very useful in real-time economic generation dispatch because they provide several generation commands for future SGs with different topologies [41]. the implementation of DL-based iterative ResBlocks improves the forecasting performance [42].

A. Long-Short-Term Memory

Recurrent neural networks (RNN) use Long Short-Term Memory. LSTM has three gates which include the forget gate, input gate, and output gate. By using the forget gate the LSTM will find out which information needs to be forgotten and which needs to be retained by using the parameter 'f_t'. This is based on the current input 'x_t', the previous output 'h_{t-1}', and the previous state 'c_{t-1}'. The forget parameter can be given by equation (1) [43]

$$f\text{t} = \sigma\,(\text{Wf}\,[xt \quad ht-1] + \text{bf}) \qquad (1)$$

where Wf and bf are the weight matrix and bias vector respectively, σ is a sigmoid function, and t and t-1 represent current and previous time respectively. Table II represents the novel research done for SG application using LSTM.

Table II. Long-Short-Term Memory applications in SG

References	Years	Sources	Application	Module/Algorithms
[43]	2022	International Journal of System Assurance Engineering and Management	Demand management	Convolution methods, Deep recurrent neural networks
[44]	2022	IET Smart Grid	Optimal price determination	Q-learning based algorithm, Pricing algorithm
[45]	2021	Journal of Network and Computer Applications	AC False Data Injection Attack detection	Logistic Regression (LR) classifier, Variational mode decomposition
[46]	2021	IEEE Transactions on Industrial Electronics	Short-term forecasting	Bi-directional LSTM(B-LSTM), Micro-clustering, Gaussian SVM.
[47]	2021	Computing and Informatics	Energy Consumption Prediction	GA-LSTM
[48]	2021	IEEE Transactions on Industrial Informatics	Short-Term Load Forecasting	Multivariable Linear Regression, LSTM NN.
[49]	2021	Computing	Quality confidence interval boundary prediction	Wavelet denoising algorithm, LSTM link quality prediction module
[50]	2021	IEEE Transactions on Cybernetics	Uncertainty-Aware Management	Multiagent-based algorithm, Consensus Algorithm, Cloud-Fog-based architecture
[51]	2021	International Journal of Sustainable Engineering	Electricity demand and price forecasting	Neural Nonlinear Autoregressive network with Exogenous variables
[52]	2020	IEEE Access	Predicting the Stability	Multidirectional LSTM
[53]	2020	Entropy	Electricity load and price forecasting	Jaya-LSTM
[54]	2019	Energies	Electricity theft detection	CNN, LSTM-NN.
[55]	2018	Dianwang Jishu/Power System Technology	Short-Term Load Forecasting	LSTM, ARIMA

The LSTM helps to determine a satisfactory, and reasonable price for customers by predicting the energy demand of customers. This provides reliable service to the customers [44]. The SG is integrated with the power grid and large-scale information and Communication Technologies and is the largest and most widely used data communication network in the IoT framework. It collects and analyzes data from distributors, transmission lines, substations, and consumer networks. The LSTM autoencoder and logistic regression classifiers identify false data injection attacks from the normal system operation events. The temporal correlations between the multi-dimensional feature vectors are used to train the LSTM-Autoencoder. [45]. A B-LSTM network is a reliable tool for time-series forecasting tasks. This handles the data with sharp variations and high stochastic behavior. The B-LSTM contains bidirectional memory-feedforward and feedback loops, which allows to see into data from previous and future hidden layers [46]. However, GA-LSTM increases the convergence speed that provides optimized effective performance, and lower execution time. This can be very useful for energy consumption prediction. When compared to random approach strategies, GA-LSTM gives better convergence. For the best answer with the least amount of error, GA constructs a new vector. [47]. The reconstruction of a new framework using the LSTM and multivariant linear regression gives better short-term load forecasting results [48]. Because of the dynamic context in which SG devices operate, the wireless link is easily disrupted, resulting in strong stochastic aspects. LSTM-NN based helps to calculate the communication link reliability confidence interval for prediction in wireless communication systems in SG [49].

Optimal prediction intervals can be constructed by using LSTM which helps in sampling data around the forecasted sample data of the SG's components. This can help in modeling a cloud-fog architecture that can be fast, feasible, flexible, reliable, and secure for modern SG [50]. Forecasting can help participants in the electricity market compete using bidding techniques. Despite its conceptual simplicity, an LSTM-based sequence-to-sequence network can estimate power consumption and pricing for smart city time-series data with high accuracy [51]. For predicting the stability of the SG, a multidimensional LSTM algorithm can be used to make cyber-physical systems [52].

The efficiency and stability of modern SG are infeasible for power load and demand forecasting. Jaya-LSTM algorithm can be used to optimize the number of epochs, batch size, and window size. In SG, the Jaya-LSTM can be used to achieve the minimum mean absolute error. Big data is utilized to forecast electricity prices and demand using LSTM. [53]. Electricity theft has one of the severe non-technical losses. A robust CNN-LSTM model can be very useful for electricity theft detection using the synthetic minority over-sampling technique. This gives better performance in recall, accuracy, and precision. CNN is a frequently used feature extraction and classification technology that automates the process [54]. The maximum information coefficient analyzes the correlation between real-time price and load and the ARIMA-based LSTM model can predict better model accuracy than the conventional model [55].

B. Recurrent Neural networks

The RNN is a special kind of ANN used for the evaluation of sequential data. It can generate the next output from the previous input. LSTM is a peculiar type of RNN which has better performance than others in predicting time-series data. This is due to the existence of the gate functions. The cell memory is represented in equation 2 [56]:

$$Ct = (Ft \otimes Ct\text{-}1) \oplus (It \otimes \tanh(WcXt + UcHt\text{-}1 + Bc)) \quad (2)$$

Where C is the cell memory, H is the hidden state, X is the input, B is bias, W and U represent the weight vectors of F and H, respectively, tanh represents the tangent function. Table III shows different application discussed in SG using RNN.

Table III. Recurrent Neural networks in smart grids

References	Year	Source	Application	Module/Algorithm
[56]	2022	IEEE Internet of Things Journal	False Data Injection Attack Detection	Backpropagation module, Kalman filter, and RNN
[57]	2019	ITT 2019 - Emerging Technologies Blockchain and IoT	Short Term Price and Load Forecasting	ANN, RNN, LSTM
[58]	2019	6th, ICCSS 2019	Optimal energy management	1-layer RNN
[59]	2019	ICEI 2019	False data detection	Residual RNN
[60]	2019	Lecture Notes in Computer Science	False Data Injection	Wide and RNN
[61]	2018	IEEE, ISGT 2018	False data injection attacks	Backpropagation learning Algorithm, RNN
[62]	2017	Journal of China Universities of Posts and Telecommunications	Anomaly detection	RNN; encoder-decoder framework
[63]	2017	IEEE, ISGT 2017	Classification	RNN, Hidden Markov Model
[64]	2016	Lecture Notes in Computer Science	Optimal real-time price	NN, Optimization, Tikhonov regularization item
[65]	2015	Neurocomputing	Optimal real-time	Lyapunov-like method, RNN.
[66]	2011	IConRAEeCE'11 - Proceedings	Faulty data identification	Hammerstein-Wiener module, Kalman filter learning algorithm.

The short-term load and price forecasting can be achieved by enhanced RNN that eliminates irrelevant features by using recursive feature elimination [57]. The battery is an important component of any SG. The absorptive ability of the battery energy storage system is different in SG as compared to the conventional energy management system. A 1-layer RNN help to solve an energy management model in SG [58]. State estimation is commonly used for the operation of SG. However, this method is not reliable during the security attacks. Yet, the residual recurrent neural network can model the anomaly and model the attack [59]. In addition, a wide and RNN model can also be used for detecting false data injection attacks [60]. The RNN-based module is superior in detecting false data injection [61]. The reliability of SG can be enhanced by detecting the anomaly in the SG. An encoder-decoder framework with RNN can detect the anomaly with an unexpected high reconstruction error [62].

To get better resilience SG it is very important to know the behavior categories of power consumers. RNN helps in the classification of consumers and makes a forecast-based classification framework [63]. Pricing is an important factor to develop an effective consumer-side management SG system. The optimized NN maximizes the aggregate utilities of all the users and minimizes the price imposed on the power provider [64]. The RNN solves the real-time price problem in the most optimized way as compared to other methods [65]. The sensor in SG holds a major role and therefore its accuracy in the system is very important. An RNN with layer feedback for each sensor provides an accuracy of the control data from different sensors. This helps to estimate the amount of fault data of the sensor by using the Kalman filter [66].

C. Convolutional Neural networks

The CNN is analogous to classic ANN as it is made up of neurons that learn to optimize. CNN has five main structures of data layer: - input to the entire NN, b) convolution layer, c) pooling layer, and d) fully connected layer [67]. In SG, the identification of faulty high-voltage power lines is very important as it leads to severe losses. These faults can happen because of several environmental hazards like severe voltage fluctuations, lighting, and incorrect design of electric field distribution. CNN and relief-F algorithms can be used to detect the power lines in SG [68]. The continuous wavelet transforms, and wavelet-CNN are used to detect the distributed denial of service attack on SG [69]. AlexNet-based deep convolution network helps in estimating the aging of conductor morphology of high-voltage electricity grid [70]. A CNN-based detector identifies distributed denial of service attacks on the electric vehicle charging station. Such a detector helps to model the demand values [71].

Ensemble DeepCNN can detect atypical behaviors of SG by using a random bagging method to deal with a highly imbalanced dataset. A random under bagging strategy is used to deal with the imbalance data as the first layer of the model, then deep CNNs are used on each subset, and lastly, a voting system is integrated as the final layer [72]. The measurement dataset included active power injection into IEEE39-buses and active power flow in the branches. A CNN algorithm mitigates the impacts of stealthy false data injection attacks in SGs [73]. Enhanced-CNN helps in modeling the uncertainties in time series [74]. For power price forecasting, CNN-based algorithms minimize data dimensionality and transmit crucial data to a classifier. Linear discriminant analysis reduces the data dimensionality and electricity price forecasting [75]. The CNN- based affinity propagation clustering algorithm and matching pursuit decomposition algorithms provide the cost-effective fault diagnosis in SG [76]. Electricity price and load forecasting provide future trends and consumption patterns. CNN-based algorithm and enhanced support vector regression give better results for electricity price and load forecasting [77]. Table IV shows the application of CNN in SG.

Table IV. Convolutional Neural networks

References	Year	Source	Application	Author Keywords
[67]	2022	Lecture Notes in Electrical Engineering	Detection of False Data Injection Cyber-Attack	CNN, Light Gradient Boosting Machine, SVM
[68]	2022	Wireless Communications and Mobile Computing	Fault Power Line Recognition	CNN, relief-F algorithm
[69]	2022	IEEE Transactions on Instrumentation and Measurement	Intelligent Aging Diagnosis of Conductor	AlexNet-based deep convolution network.
[70]	2021	18th ICCWAMTIP 2021	Detecting Cyber Attack of Distributed Denial of Service	Continuous wavelet transform, wavelet CNN
[71]	2021	2021, ISNCC 2021	Detection of Denial of Charge Attacks	Hyper-Parameter Optimization, CNN
[72]	2020	IEEE Conference Cybernetics	Electricity Theft Detection	Ensemble Deep-CNN
[73]	2020	ICEIEC 2020 -	Mitigating the Impacts of False Data Injection Attacks	CNN
[74]	2020	Systems and Computing	Electricity Price Forecasting	Relief-F, Multilayer Perceptron, Enhanced CNN, and SVM.
[75]	2020	Intelligent Systems and Computing	Electricity Price Forecasting	Linear Discriminant Analysis, Enhanced CNN
[76]	2019	18th IEEE, ICMLA 2019	Diagnosing faults	Clustering algorithm, Matching pursuit decomposition, Affinity propagation clustering algorithm
[77]	2019	Electronics (Switzerland)	Electricity price and load forecasting	Enhanced CNN, Enhanced support vector regression
[78]	2019	WSEAS Transactions on Power Systems	Source-load forecasting	CNN
[79]	2019	Lecture Notes	Price forecasting	Fusing XG-Boost, DT, Enhanced CNN, Enhanced support vector regression
[80]	2018	IEEE Transactions of Informatics	Electricity-Theft Detection	SVM, CNN

The CNN-based algorithm provides an energy management system by forecasting renewable energy resources [78]. The hybrid of CNN-based fusing XG-Boost and DT can be used to create a model for forecasting price. This constitutes in feature engineering, and classification. The enhanced CNN and support vector regression can be used in classification to evaluate the model performance [79]. The wide and deep CNN model performs best among the existing model in case of electricity theft in SG [80]. Although the [81,82] represents some advanced deep learning and machine learning methods in smart grid, a wide range of state-of-the-art methods of machine learning, e.g., [83-94], are yet to be experimented. From the hybrid methods of deep learning and machine learning to the ensemble and optimized machine learning methods, e.g., [95-109], numerous techniques have not yet been applied in the smart grid applications. For the future research using such methods for developing advanced models are suggested.

CONCLUSION

Major deep learning methods for smart grid had been represented and a new taxonomy presented. The study showed that three major deep learning method of RNN, CNN and LSTM had the most applications among the other deep learning methods. These algorithms are best suitable for risk management analysis, forecasting, electricity theft, anomaly detection, false data injection attacks and cyber security.

List of Acronyms

SG	Smart Grid
ML	Machine Learning
DL	Deep Learning
LSTM	Long-Short-Term Memory
DNN	Deep Neural Network
RNN	Recurrent Neural Network
SVM	Support Vector Machine
CNN	Convolutional Neural Network
ANN	Artificial Neural Network
FDIA	False Data Injection Attacks
RF	Random Forest
IoT	Internet of Things
B-LSTM	Bi-directional-LSTM
DSM	Demand Side Management

REFERENCES

[1] Huang, G., Wu, F., Guo, C. Smart grid dispatch powered by deep learning: a survey (2022) Frontiers of Information Technology and Electronic Engineering

[2] Elahe, M.F., Jin, M., Zeng, P. Review of load data analytics using deep learning in smart grids: Open load datasets, methodologies, and application challenges (2021) International Journal of Energy Research.

[3] Kotsiopoulos, T., Sarigiannidis, P., Ioannidis, D., Tzovaras, D. Machine Learning and Deep Learning in smart manufacturing: The Smart Grid paradigm (2021) Computer Science Review.

[4] De La Torre Parra, G., Rad, P., Choo, K.-K.R. Implementation of deep packet inspection in smart grids and industrial Internet of Things: Challenges and opportunities (2019) Journal of Network and Computer Applications.

[5] Majidi, S.H., Hadayeghparast, S., Karimipour, H. FDI attack detection using extra trees algorithm and deep learning algorithm-autoencoder in smart grid (2022) International Journal of Critical Infrastructure Protection.

[6] H.S., S., Ramaiah, N.S. A two-stage deep convolutional model for demand response energy management system in IoT-enabled smart grid (2022) Sustainable Energy, Grids and Networks.

[7] Yin, L., Lu, Y. Expandable quantum deep width learning-based distributed voltage control for smart grids with high penetration of distributed energy resources (2022) International Journal of Electrical Power and Energy Systems.

[8] Hao, J., Tao, Y. Adversarial attacks on deep learning models in smart grids (2022) Energy Reports.

[9] Wang, Y., Zhang, Z., Ma, J., Jin, Q. KFRNN: An Effective False Data Injection Attack Detection in Smart Grid Based on Kalman Filter and Recurrent Neural Network(2022) IEEE Internet of Things Journal.

[10] Xu, B., Guo, F., Zhang, W.-A., Li, G., Wen, C. E2DNet: An Ensembling Deep Neural Network for Solving Nonconvex Economic

Dispatch in Smart Grid (2022) IEEE Transactions on Industrial Informatics.

[11] Teng, T., Ma, L.Deep learning-based risk management of financial market in smart grid(2022) Computers and Electrical Engineering.

[12] Li, H., Shen, Y., Luo, Y. Transient security situational awareness of smart grids based on an improved deep belief network(2022) Dianli Xitong Baohu yu Kongzhi/Power System Protection and Control.

[13] Yin, X., Zhu, Y., Hu, J. A Subgrid-Oriented Privacy-Preserving Microservice Framework Based on Deep Neural Network for False Data Injection Attack Detection in Smart Grids(2022) IEEE Transactions on Industrial Informatics.

[14] Khan, I.U., Javeid, N., Taylor, C.J., Gamage, K.A.A., Ma, X. A Stacked Machine and Deep Learning-Based Approach for Analysing Electricity Theft in Smart Grids(2022) IEEE Transactions on Smart Grid.

[15] Ardabili S, Mosavi A, Dehghani M, Várkonyi-Kóczy AR. Deep learning and machine learning in hydrological processes climate change and earth systems a systematic review. InInternational conference on global research and education 2019 Sep 4 (pp. 52-62). Springer, Cham.

[16] Mosavi A, Faghan Y, Ghamisi P, Duan P, Ardabili SF, Salwana E, Band SS. Comprehensive review of deep reinforcement learning methods and applications in economics. Mathematics. 2020 Oct;8(10):1640.

[17] Ardabili S, Mosavi A, Várkonyi-Kóczy AR. Systematic review of deep learning and machine learning models in biofuels research. InInternational Conference on Global Research and Education 2019 Sep 4 (pp. 19-32). Springer, Cham.

[18] Ayub S, Guan BH, Ahmad F, Oluwatobi YA, Nisa ZU, Javed MF, Mosavi A. Graphene and iron reinforced polymer composite electromagnetic shielding applications: A review. Polymers. 2021 Jan;13(15):2580.

[19] Ayub S, Guan BH, Ahmad F, Javed MF, Mosavi A, Felde I. Preparation Methods for Graphene Metal and Polymer Based Composites for EMI Shielding Materials: State of the Art Review of the Conventional and Machine Learning Methods. Metals. 2021 Aug;11(8):1164.

[20] Mohammed AA, Ahmed HU, Mosavi A. Survey of Mechanical Properties of Geopolymer Concrete: A Comprehensive Review and Data Analysis. Materials. 2021 Jan;14(16):4690.

[21] Amanlou A, Suratgar AA, Tavoosi J, Mohammadzadeh A, Mosavi A. Single-Image Reflection Removal Using Deep Learning: A Systematic Review. IEEE Access. 2022 Mar 2.

[22] Ahmed HU, Mohammed AA, Rafiq S, Mohammed AS, Mosavi A, Sor NH, Qaidi S. Compressive Strength of Sustainable Geopolymer Concrete Composites: A State-of-the-Art Review. Sustainability. 2021 Jan;13(24):13502.

[23] Tabrizchi H, Razmara J, Mosavi A, Varkonyi-Koczy AR. Deep Learning Applications for COVID-19: A Brief Review. InInternational Conference on Global Research and Education 2022 (pp. 117-130). Springer, Singapore.

[24] Mosavi A, Ardabili S, Varkonyi-Koczy AR. List of deep learning models. InInternational Conference on Global Research and Education 2019 Sep 4 (pp. 202-214). Springer, Cham.

[25] Ardabili S, Mosavi A, Várkonyi-Kóczy AR. Building Energy information: demand and consumption prediction with Machine Learning models for sustainable and smart cities. InInternational Conference on Global Research and Education 2019 Sep 4 (pp. 191-201). Springer, Cham.

[26] Ardabili Sina, Abdolalizadeh Leila, Mako Csaba, Torok Bernat, Mosavi Amir, Systematic Review of Deep Learning and Machine Learning for Building Energy, Frontiers in Energy Research , 10, 2022, DOI=10.3389/fenrg.2022.786027.

[27] Mosavi A, Ozturk P, Chau KW. Flood prediction using machine learning models: Literature review. Water. 2018 Nov;10(11):1536.

[28] Teng, T., Ma, L. Deep learning-based risk management of financial market in smart grid(2022) Computers and Electrical Engineering.

[29] Mukherjee, D., Chakraborty, S., Ghosh, S. Deep learning-based multilabel classification for locational detection of false data injection attack in smart grids(2022) Electrical Engineering.

[30] Menon, D.M., Radhika, N. A Trust-Based Framework and Deep Learning-Based Attack Detection for Smart Grid Home Area Network (2022) International Journal of Intelligent Engineering and Systems.

[31] Sengan, S., V, S., V, I., Velayutham, P., Ravi, L. Detection of false data cyber-attacks for the assessment of security in smart grid using deep learning(2021) Computers and Electrical Engineering.

[32] Jeyaraj, P.R., Nadar, E.R.S. Computer-assisted demand-side energy management in residential smart grid employing novel pooling deep learning algorithm(2021) International Journal of Energy Research.

[33] Tian, Y., Wang, Q., Guo, Z., Zhao, H., Khan, S., Mao, W., Yasir, M., Zhao, J. A hybrid deep learning and ensemble learning mechanism for damaged power line detection in smart grids(2021) Soft Computing.

[34] Reka, S.S., Venugopal, P., Alhelou, H.H., Siano, P., Golshan, M.E.H. Real Time Demand Response Modeling for Residential Consumers in Smart Grid Considering Renewable Energy with Deep Learning Approach(2021) IEEE Access.

[35] Massaoudi, M., Abu-Rub, H., Refaat, S.S., Chihi, I., Oueslati, F.S. Deep Learning in Smart Grid Technology: A Review of Recent Advancements and Future Prospects(2021) IEEE Access.

[36] Yang, Y., Yang, Z., Yu, J., Xie, K., Jin, L. Fast Economic Dispatch in Smart Grids Using Deep Learning: An Active Constraint Screening Approach(2020) IEEE Internet of Things Journal.

[37] Velasco, J.A., Amaris, H., Alonso, M. Deep Learning loss model for large-scale low voltage smart grids(2020) International Journal of Electrical Power and Energy Systems.

[38] Jeyaraj, P.R., Nadar, E.R.S., Kathiresan, A.C., Asokan, S.P. Smart grid security enhancement by detection and classification of non-technical losses employing deep learning algorithm(2020) International Transactions on Electrical Energy Systems.

[39] Yang, Y., Li, W., Gulliver, T.A., Li, S. Bayesian Deep Learning-Based Probabilistic Load Forecasting in Smart Grids(2020) IEEE Transactions on Industrial Informatics.

[40] Hafeez, G., Alimgeer, K.S., Wadud, Z., Shafiq, Z., Khan, M.U.A., Khan, I., Khan, F.A., Derhab, A. A novel accurate and fast converging deep learning-based model for electrical energy consumption forecasting in a smart grid (2020) Energies.

[41] Yin, L., Gao, Q., Zhao, L., Wang, T. Expandable deep learning for real-time economic generation dispatch and control of three-state energies based future smart grids(2020) Energy.

[42] Hong, Y., Zhou, Y., Li, Q., Xu, W., Zheng, X. A deep learning method for short-term residential load forecasting in smart grid(2020) IEEE Access.

[43] Perumal, S., Rajendiran, S. Low power multiplier based long short-term memory hardware architecture for smart grid energy management (2022) International Journal of System Assurance Engineering and Management.

[44] Mousavi Ziabari, Z., Pasdar, A. Prediction using long short-term memory networks in the service of designing a novel pricing policy for smart grid (2022) IET Smart Grid.

[45] Yang, L., Zhai, Y., Li, Z. Deep learning for online AC False Data Injection Attack detection in smart grids: An approach using LSTM-Autoencoder (2021) Journal of Network and Computer Applications.

[46] Jahangir, H., Tayarani, H., Gougheri, S.S., Golkar, M.A., Ahmadian, A., Elkamel, A. Deep Learning-Based Forecasting Approach in Smart Grids with Microclustering and Bidirectional LSTM Network (2021) IEEE Transactions on Industrial Electronics.

[47] Kumari, S., Kumar, N., Rana, P.S. Big data analytics for energy consumption prediction in smart grid using genetic algorithm and long short term memory (2021) Computing and Informatics.

[48] Li, J., Deng, D., Zhao, J., Cai, D., Hu, W., Zhang, M., Huang, Q. A Novel Hybrid Short-Term Load Forecasting Method of Smart Grid Using MLR and LSTM Neural Network (2021) IEEE Transactions on Industrial Informatics.

[49] Sun, W., Li, P., Liu, Z., Xue, X., Li, Q., Zhang, H., Wang, J. LSTM based link quality confidence interval boundary prediction for wireless communication in smart grid (2021) Computing.

[50] Tajalli, S.Z., Kavousi-Fard, A., Mardaneh, M., Khosravi, A., Razavi-Far, R. Uncertainty-Aware Management of Smart Grids Using Cloud-Based LSTM-Prediction Interval (2021) IEEE Transactions on Cybernetics.

[51] Fatema, I., Kong, X., Fang, G. Electricity demand and price forecasting model for sustainable smart grid using comprehensive long short term memory (2021) International Journal of Sustainable Engineering,

[52] Alazab, M., Khan, S., Krishnan, S.S.R., Pham, Q.-V., Reddy, M.P.K., Gadekallu, T.R. A Multidirectional LSTM Model for Predicting the Stability of a Smart Grid (2020) IEEE Access.

[53] Khalid, R., Javaid, N., Al-zahrani, F.A., Aurangzeb, K., Qazi, E.-U.-H., Ashfaq, T. Electricity load and price forecasting using jaya-long short term memory (JLSTM) in smart grids (2020) Entropy.

[54] Nazmul Hasan, Md., Toma, R.N., Nahid, A.-A., Manjurul Islam, M.M., Kim, J.-M. Electricity theft detection in smart grid systems: A CNN-LSTM based approach (2019) Energies.

[55] Li, P., He, S., Han, P., Zheng, M., Huang, M., Sun, J. Short-Term Load Forecasting of Smart Grid Based on Long-Short-Term Memory Recurrent Neural Networks in Condition of Real-Time Electricity Price (2018) Dianwang Jishu/Power System Technology.

[56] Wang, Y., Zhang, Z., Ma, J., Jin, Q. KFRNN: An Effective False Data Injection Attack Detection in Smart Grid Based on Kalman Filter and Recurrent Neural Network (2022) IEEE Internet of Things Journal.

[57] Usman, M., Ali Khan, Z., Khan, I.U., Javaid, S., Javaid, N. Data Analytics for Short Term Price and Load Forecasting in Smart Grids using Enhanced Recurrent Neural Network (2019) ITT 2019 - Information Technology Trends: Emerging Technologies Blockchain and IoT.

[58] Sun, M., He, X. A recurrent neural network for optimal energy management considering the battery cycle-life in smart grid (2019) 2019 6th International Conference on Information, Cybernetics, and Computational Social Systems, ICCSS 2019.

[59] Wang, Y., Shi, W., Jin, Q., Ma, J. An accurate false data detection in smart grid based on residual recurrent neural network and adaptive threshold (2019) Proceedings - IEEE International Conference on Energy Internet, ICEI 2019.

[60] Wang, Y., Chen, D., Zhang, C., Chen, X., Huang, B., Cheng, X. Wide and Recurrent Neural Networks for Detection of False Data Injection in Smart Grids (2019) Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics).

[61] Ayad, A., Farag, H.E.Z., Youssef, A., El-Saadany, E.F. Detection of false data injection attacks in smart grids using Recurrent Neural Networks (2018) 2018 IEEE Power and Energy Society Innovative Smart Grid Technologies Conference, ISGT 2018.

[62] Fengming, Z., Shufang, L., Zhimin, G., Bo, W., Shiming, T., Mingming, P. Anomaly detection in smart grid based on encoder-decoder framework with recurrent neural network (2017) Journal of China Universities of Posts and Telecommunications.

[63] Taherei Ghazvinei, P., et al., 2018. Sugarcane growth prediction based on meteorological parameters using extreme learning machine and artificial neural network. Engineering Applications of Computational Fluid Mechanics, 12(1), pp.738-749.

[64] Kalbasi, R., et al., 2021. Finding the best station in Belgium to use residential-scale solar heating, one-year dynamic simulation with considering all system losses: economic analysis of using ETSW. Sustainable Energy Technologies and Assessments, 45, p.101097.

[65] Tornai, K., Olah, A., Drenyovszki, R., Kovacs, L., Pinte, I., Levendovszky, J. Recurrent neural network based user classification for smart grids (2017) 2017 IEEE Power and Energy Society Innovative Smart Grid Technologies Conference, ISGT 2017.

[66] Niu, H., Wang, Z., Liu, Z., Zhang, Y. Optimal real-time price in smart grid via recurrent neural network (2016) Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics).

[67] He, X., Huang, T., Li, C., Che, H., Dong, Z. A recurrent neural network for optimal real-time price in smart grid (2015) Neurocomputing.

[68] Raju, A.D.J., Manohar, S.S. Recurrent neural network for faulty data identification in smart grid (2011) 2011 International Conference on Recent Advancements in Electrical, Electronics and Control Engineering, IConRAEeCE'11 - Proceedings,

[69] Khan, A. Detection of False Data Injection Cyber-Attack in Smart Grid by Convolutional Neural Network-Based Deep Learning Technique (2022) Lecture Notes in Electrical Engineering.

[70] Yuqing, Z. A Hybrid Convolutional Neural Network and Relief-F Algorithm for Fault Power Line Recognition in Internet of Things-Based Smart Grids (2022) Wireless Communications and Mobile Computing.

[71] Yi, Y., Chen, Z., Wang, L. Intelligent Aging Diagnosis of Conductor in Smart Grid Using Label-Distribution Deep Convolutional Neural Networks (2022) IEEE Transactions on Instrumentation and Measurement.

[72] Monday, H.N., Li, J.P., Nneji, G.U., Yutra, A.Z., Lemessa, B.D., Nahar, S., James, E.C., Haq, A.U. The Capability of Wavelet Convolutional Neural Network for Detecting Cyber Attack of Distributed Denial of Service in Smart Grid (2021) 2021 18th International Computer Conference on Wavelet Active Media Technology and Information Processing, ICCWAMTIP 2021.

[73] Shafee, A., Nabil, M., Mahmoud, M., Alasmary, W., Amsaad, F. Detection of Denial of Charge (DoC) Attacks in Smart Grid Using Convolutional Neural Networks (2021) 2021 International Symposium on Networks, Computers and Communications, ISNCC 2021.

[74] Rouzbahani, H.M., Karimipour, H., Lei, L. An Ensemble Deep Convolutional Neural Network Model for Electricity Theft Detection in Smart Grids (2020) Conference Proceedings - IEEE International Conference on Systems, Man and Cybernetics.

[75] Ge, Q., Jiao, C. Mitigating the Impacts of False Data Injection Attacks in Smart Grids using Deep Convolutional Neural Networks (2020) ICEIEC 2020 - Proceedings of 2020 IEEE 10th International Conference on Electronics Information and Emergency Communication.

[76] Adil, M., Javaid, N., Daood, N., Asim, M., Ullah, I., Bilal, M. Big Data Based Electricity Price Forecasting Using Enhanced Convolutional Neural Network in the Smart Grid (2020) Advances in Intelligent Systems and Computing.

[77] Daood, N., Khan, Z.A., Ashrafullah, Khan, M.J., Adil, M., Javaid, N. Electricity Price Forecasting Based on Enhanced Convolutional Neural Network in Smart Grid (2020) Advances in Intelligent Systems and Computing,

[78] Hassani, H., Farajzadeh-Zanjani, M., Razavi-Far, R., Saif, M., Palade, V. Design of a cost-effective deep convolutional neural network-based scheme for diagnosing faults in smart grids (2019) Proceedings - 18th IEEE International Conference on Machine Learning and Applications, ICMLA 2019.

[79] Zahid, M., Ahmed, F., Javaid, N., Abbasi, R.A., Kazmi, H.S.Z., Javaid, A., Bilal, M., Akbar, M., Ilahi, M. Electricity price and load forecasting using enhanced convolutional neural network and enhanced support vector regression in smart grids (2019) Electronics (Switzerland).

[80] Khoury, D., Keyrouz, F. A predictive convolutional neural network model for source-load forecasting in smart grids (2019) WSEAS Transactions on Power Systems.

[81] Ahmed, F., Zahid, M., Javaid, N., Khan, A.B.M., Khan, Z.A., Murtaza, Z. A Deep Learning Approach Towards Price Forecasting Using Enhanced Convolutional Neural Network in Smart Grid (2019) Lecture Notes on Data Engineering and Communications Technologies.

[82] Zheng, Z., Yang, Y., Niu, X., Dai, H.-N., Zhou, Y. Wide and Deep Convolutional Neural Networks for Electricity-Theft Detection to Secure Smart Grids (2018) IEEE Transactions on Industrial Informatics.

[83] Torabi, M., et al., (2019). A Hybrid clustering and classification technique for forecasting short - term energy consumption. Environmental progress & sustainable energy, 38(1), 66-76.

[84] Emadi, M., et al., 2020. Predicting and mapping of soil organic carbon using machine learning algorithms in Northern Iran. Remote Sensing, 12(14), p.2234.

[85] Lei, X., et al., 2020. GIS-based machine learning algorithms for gully erosion susceptibility mapping in a semi-arid region of Iran. Remote Sensing, 12(15), p.2478.

[86] Band, S.S., et al., 2020. Flash flood susceptibility modeling using new approaches of hybrid and ensemble tree-based machine learning algorithms. Remote Sensing, 12(21), p.3568.

[87] Band, S.S., et al., 2020. Novel ensemble approach of deep learning neural network (DLNN) model and particle swarm optimization (PSO) algorithm for prediction of gully erosion susceptibility. Sensors, 20(19), p.5609.

[88] Rezakazemi, M., et al., 2019. ANFIS pattern for molecular membranes separation optimization. Journal of Molecular Liquids, 274, pp.470-476.

[89] Seifi, A., et al., 2020. Modeling and uncertainty analysis of groundwater level using six evolutionary optimization algorithms hybridized with ANFIS, SVM, and ANN. Sustainability, 12(10), p.4023.

[90] Mahmoudi, M.R., et al., 2021. Principal component analysis to study the relations between the spread rates of COVID-19 in high risks countries. Alexandria Engineering Journal, 60(1), pp.457-464.

[91] Choubin, B., et al., 2019. Earth fissure hazard prediction using machine learning models. Environmental research, 179, p.108770.

[92] Ghalandari, M., et al., 2019. Flutter speed estimation using presented differential quadrature method formulation. Engineering Applications of Computational Fluid Mechanics, 13(1), pp.804-810.

[93] Sadeghzadeh, M., et al., 2020. Prediction of thermo-physical properties of TiO2-Al2O3/water nanoparticles by using artificial neural network. Nanomaterials, 10(4), p.697.

[94] Shabani, S., et al., 2020. Modeling pan evaporation using Gaussian process regression K-nearest neighbors random forest and support vector machines; comparative analysis. Atmosphere, 11(1), p.66.

[95] Nabipour, M., et al., 2020. Predicting stock market trends using machine learning and deep learning algorithms via continuous and binary data; a comparative analysis. IEEE Access, 8, pp.150199-150212

[96] Mosavi, A., et al., 2020. Comprehensive review of deep reinforcement learning methods and applications in economics. Mathematics, 8(10), p.1640.

[97] Mousavi, S.M., et al., 2021. Deep learning for wave energy converter modeling using long short-term memory. Mathematics, 9(8), p.871.

[98] Dehghan Manshadi, M., et al., 2021. Predicting the Parameters of Vortex Bladeless Wind Turbine Using Deep Learning Method of Long Short-Term Memory. Energies, 14(16), p.4867.

[99] Ardabili Sina, et al., Systematic Review of Deep Learning and Machine Learning for Building Energy, Frontiers in Energy Research, V. 10, 2022, DOI=10.3389/fenrg.2022.786027

[100] Ardabili, S., et al., 2019, September. Advances in machine learning modeling reviewing hybrid and ensemble methods. In International Conference on Global Research and Education (pp. 215-227). Springer, Cham.

[101] Mohammadzadeh S, D., et al., 2019. Prediction of compression index of fine-grained soils using a gene expression programming model. Infrastructures, 4(2), p.26.

[102] Ghalandari, M., et al., 2019. Aeromechanical optimization of first row compressor test stand blades using a hybrid machine learning model of genetic algorithm, artificial neural networks and design of experiments. Engineering Applications of Computational Fluid Mechanics, 13(1), pp.892-904.

[103] Qasem, S.N., et al., 2019. Estimating daily dew point temperature using machine learning algorithms. Water, 11(3), p.582.

[104] Joloudari, J.H., et al., 2020. Coronary artery disease diagnosis; ranking the significant features using a random trees model. International journal of environmental research and public health, 17(3), p.731.

[105] Mosavi, A., Sajedi Hosseini, F., Choubin, B., Goodarzi, M., Dineva, A.A. and Rafiei Sardooi, E., 2021. Ensemble boosting and bagging based machine learning models for groundwater potential prediction. Water Resources Management, 35(1), pp.23-37.

[106] Asadi, E., et al., 2020. Groundwater quality assessment for sustainable drinking and irrigation. Sustainability, 12(1), p.177.

[107] Ahmadi, M.H., et al., 2020. Evaluation of electrical efficiency of photovoltaic thermal solar collector. Engineering Applications of Computational Fluid Mechanics, 14(1), pp.545-565.

[108] Shamshirband, S., et al., 2020. Prediction of significant wave height; comparison between nested grid numerical model, and machine learning models of artificial neural networks, extreme learning and support vector machines. Engineering Applications of Computational Fluid Mechanics, 14(1), pp.805-817.

[109] Nabipour, N., et al., 2020. Modeling climate change impact on wind power resources using adaptive neuro-fuzzy inference system. Engineering Applications of Computational Fluid Mechanics, 14(1), pp.491-506.