

SMART GRIDS DATA ANALYSIS WITH ARTIFICIAL INTELLIGENCE

Rituraj R. , Kanatova A. ^{*} , Shayakhmetov A. ,
Baipakbayeva S. , Golovachyova V. , Varkonyi-Koczy A. , Mosavi A. ^{*} 

Abstract Artificial intelligence is applied in smart grids to improve efficiency, reliability, and the integration of conventional and renewable energy sources. A state of the art review of artificial intelligence methods in smart grids is presented. A methodology is used for resource identification and systematic review. A taxonomy is proposed to classify machine learning models by method and application domain. Models are compared based on accuracy and computational efficiency. Key applications such as demand response, energy forecasting, fault detection, and grid optimization are analyzed. Artificial neural networks, decision trees, long short term memory networks, support vector machines, convolutional neural networks, and random forest models are identified as the most used approaches. The best performance is reported for convolutional neural network based and random forest based models. Load forecasting and energy management are identified as the most common application areas.

Key words: artificial intelligence, machine learning, deep learning, smart grids, review, data science, big data, reinforcement learning, explainable artificial intelligence, edge computing, Internet of Things, predictive analytics

AMS Mathematics Subject Classification: 68T07, 90C26, 62M45.

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1 Introduction

Artificial intelligence (AI) is considered essential in smart grid (SG) management because real time decisions are required in large and complex electricity networks. Demand forecasting, grid optimization, renewable energy source (RES) integration, fault detection, and demand response (DR) are enhanced through AI. Grid reliability, efficiency, adaptability, and sustainability are therefore improved [1]. The SG is defined as an advanced electricity grid in which digital technologies are applied to deliver electricity reliably, securely, and efficiently. Bidirectional communication between utilities and consumers is enabled, and supply and demand are controlled in real time. RES integration, electric vehicle use, distributed energy resources, battery storage, and DR programs are also supported. Dependence on fossil fuels is reduced, and environmental sustainability is improved. Major SG opportunities and challenges are widely reported. RES integration and investment in transmission, control, measurement, and software are identified as significant issues [2]. Adaptation to internal and external changes is required, and cascading failure risk in interconnected grids is emphasized [3]; [4]. Consumer participation, home energy management, two way power and information exchange, new markets, storage, and rural benefits are also highlighted [5]. Capacity, efficiency, dependability, sustainability, rising demand, environmental compatibility of RESs, reliability pressure, and network reinforcement are identified as key drivers [6]; [7]; [8]. The traditional grid delivers electricity in one direction from large plants to consumers. In contrast, the SG supports two way communication, RES integration, distributed energy resources, electric vehicles, and stronger cyber protection. Figure 1 illustrates this difference. Bidirectional information flow is provided in the SG, whereas it is absent in the traditional grid.

¹Corresponding Author.

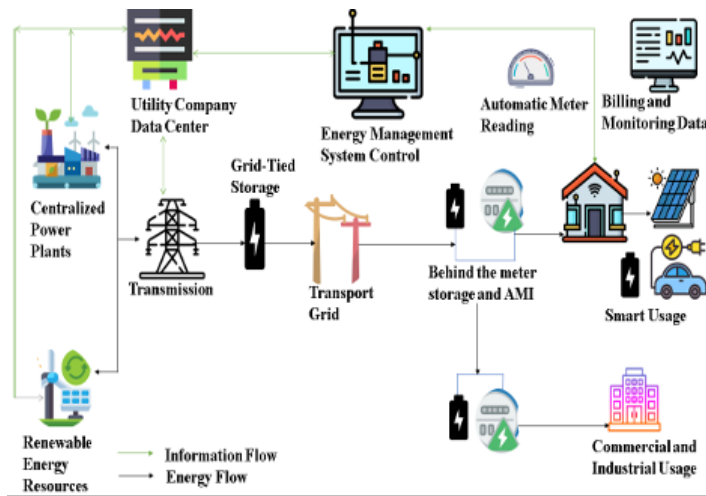


Figure 1: SG architecture overview.

Wider use of advanced computational methods in SGs is also reported. Secure cyber physical connectivity is required for condition monitoring, and machine learning (ML) and deep learning (DL) are shown to deliver strong results in many SG tasks [9]. Model interpretability is required because SG infrastructure is critical [10]. Outages are caused by severe weather, network damage, and demand fluctuation, and large data volume requires dynamic energy management, monitoring, real time operation, and production planning [11]; [12]. Suitable analytical tools for grid elements and power converters are also supported through ML and DL methods [13]. Serious security and operational challenges are also reported. Cyber attacks can target electricity delivery, billing, and unauthorized access, with financial and reputational loss as a result [9]. Expert uncertainty remains because ML error can affect critical decisions during power failure [10]. Prosumers, blockchain, supervisory control and data acquisition (SCADA) data processing, voltage stability assessment, smart city planning, home automation, and DR are examined in recent SG studies [14]; [15]; [16]; [17]. Disturbances, fifth generation (5G) support, specialized algorithms, false data injection (FDI) attacks, cloud based forecasting, load and price forecasting, renewable transition challenges, electric vehicles, and AI based demand forecasting are also emphasized [18]. Figure 2 presents major AI, computational intelligence, and ML applications in SGs.

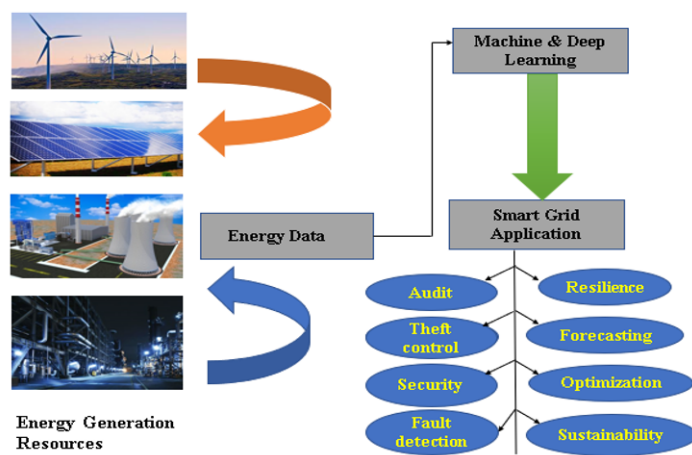


Figure 2: Application of ML in SG.

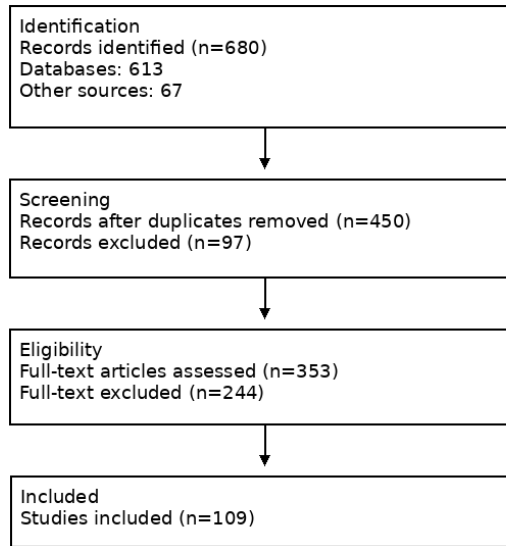


Figure 3: PRISMA Flowchart

1 Methodology

The literature classification and the research approach of this review are described in this section. Related studies are collected and are classified under predefined categories. The article is organized into six sections. An introduction is first provided. ANN, support vector machine (SVM), extreme learning machine (ELM), decision tree (DT), random forest (RF), and logistic regression (LR) are then reviewed. Evaluation criteria, building energy demand prediction results, and ML applications in SGs are also discussed comparatively. The Preferred Reporting Items for Systematic Reviews and Meta Analyses (PRISMA) standard is used for data collection. Four stages are defined, namely identification, screening, eligibility, and inclusion. In the identification stage, 680 relevant articles are retrieved from Elsevier Scopus. Duplicate records are then removed, and titles and abstracts are screened. After full text assessment, 109 articles are selected for detailed evaluation. Finally, a database is constructed for qualitative and quantitative analysis, and 201 publications are included. Figure ?? shows the PRISMA flowchart.

Artificial Neural Networks

Artificial neural network (ANN) models are ML methods derived from the structure of the human brain. Wide use is reported in SGs because nonlinear data and complex relations are handled effectively. ANN models are applied to load forecasting (LF), fault detection, and energy management. Grid efficiency, reliability, and sustainability are therefore improved. ANN training is treated as the main stage of network creation. Data are transferred between neurons through weighted connections, as shown in Equation (1) [19].

$$I_j(t) = \sum_i O_i(t)w_{ij} + w_{oj} \quad (1)$$

Here, I_j is the input value from neuron i to neuron j , O_i is the output of neuron i , w_{ij} is the weight value, and w_{oj} is the bias of neuron j . A basic ANN structure is shown in Figure 4. Training, testing, and validation are the main ANN stages.

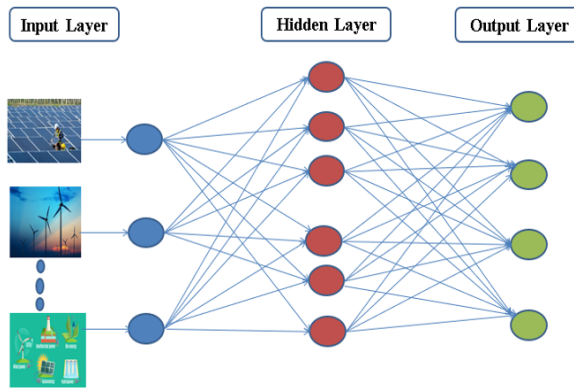


Figure 4: Basic architecture of ANN.

ANN is described as a data driven ML method based on biological neurons [20]. Self organized maps, radial basis function networks, multilayer perceptrons, and back propagation are reported as major ANN forms [21]; [22]; [23]. ANN applications are also reported for material selection, photovoltaic fault detection, building energy use, RES maintenance, wind energy, partial discharge recognition, demand side management, and solar radiation prediction [24]; [25]; [26]; [27]; [28]; [29]; [30]; [31]; [32].

The SG studies report ANN use in attack detection, 5G and zero trust security, DR load shifting, multi source energy management, FDI analysis, intrusion detection, reactive power control, and failure prediction [33]. Hybrid ANN models are also reported for short term LF, cost analysis, home energy management, islanding detection, and technical loss reduction [41].

Support Vector Machines

Support vector machine (SVM) models are supervised learning methods for classification and regression. In SGs, SVM models are applied to LF, fault detection, and power quality classification. High dimensional data, small datasets, noise, and nonlinear relations can be handled effectively. Good predictive performance is therefore often achieved. SVM is formulated as a maximum margin classifier. The hyperplane separates classes, and support vectors determine its position. Equation (2) defines the hyperplane [46].

$$\vec{\omega} \cdot \vec{x}_1 - b = 0. \quad (2)$$

Here, $\vec{\omega}$ is the normal vector, and $\frac{b}{\omega}$ is the offset from the origin. Soft and hard margins are defined in SVM. The soft margin form is shown in Equation (3) [47].

$$\left[\frac{1}{n} \sum_{i=1}^n \max(0, 1 - y_i(\vec{\omega} \cdot \vec{x}_i - b)) \right] + \lambda \|\vec{\omega}\|^2. \quad (3)$$

Here, λ denotes the trade off between margin size and correct classification. Figure 5 shows the separating support vectors.

Table 1: Novel work based on ANN-based method in SG

Ref.	Contribution	Application	Source	ANN-Based Method
[33]	Securing SG data	Data security	Neural Processing Letters	Salp Swarm Optimization, Discrete Wavelet Transform
[34]	Reducing the security risks of 5G IoT in SG	Information security	Frontiers in Computational Neuroscience	Intelligent link state algorithm, Improved multiple protection model
[35]	Solving the load shifting from the DR	Customer incentive pricing	IET Smart Grid	Sliding time window technique, Genetic algorithm
[36]	Safety of electricity to consumers with a maximum solicitation of renewable energy	Multiple-source energy management	International Journal of Power Electronics and Drive Systems	Multilayer perceptron network
[37]	Deploying a hybrid ML model to mitigate false attacks in SG	Security	Computers and Security	Gradient-based and Population-based algorithm
[38]	Proposing a cyber detection approach to identify cyber intrusion in the SG	False data detection system	International Journal of Engineering, Transactions B: Applications	Intelligent Loop Based-ANN
[39]	Designing RESs-based SG to maintain an improved voltage profile with a balanced reactive power level	Reactive power control	Energy Sources, Part A	Feed Forward NN, MPPT algorithm
[40]	Creating an intrusion detection model to classify multi-class cyber-attacks and power-system incidents	Attacks Challenges, Failure prediction, and detection in a power system	Neural Computing and Applications	Whale optimization algorithm, Multilayer perceptron
[41]	Improving the overall system performance and quality in SG.	LF	Electric Power Systems Research	Kalman filtering, Wavelet, and ANN
[42]	Finding a low tariff area and intercepting the creation of minimal-price peaks	Optimization of load demand and storage management	Energies	Load-based pricing policy algorithm, Genetic algorithm, Particle swarm optimization
[43]	Forecasting demand response and energy consumption using a home energy management controller	Energy Management	IEEE Access	Day-ahead grey wolf modified enhanced differential evolution algorithm, Day-ahead genetic algorithm
[44]	Providing synchronized phasor measurements from a power system.	Islanding detection	IET Generation, Transmission, and Distribution	Andrews plot-based method, multiplier-based method, dimension reduction algorithms
[45]	Reducing the technical losses of the capacitor banks present in the grid.	Technical loss detection	Brazilian Archives of Biology and Technology	SINAP grid program with ANN algorithm

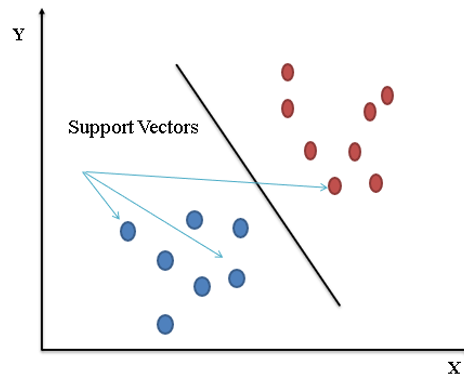


Figure 5: Support vectors of SVM algorithms differentiating the data clusters.

Strong SVM performance with small datasets, hybrid ANN SVM prediction, intrusion detection, solar and wind forecasting, electricity price estimation, diffuse solar radiation estimation, twin SVM, and real world engineering applications are reported in prior studies [48]; [49]; [50]; [51]; [52]; [53]; [54]; [55]; [56].

Table 2: Novel work based on SVM-based method in SG

Ref.	Contribution	Application	Source	SVM-based methods
[57]	Multi-objective optimal dispatching of SG	Forecasting the actual load	Mobile Information Systems	Multi-particle swarm optimization, SVM
[58]	Detecting and identifying a multi-complex electric power quality event in SG	Non-stationary signal detection	Electrical Engineering	Hilbert–Huang transform-SVM
[59]	Utilization inspection for filtered information	False data filtering	International Journal of Internet Protocol Technology	SVM-based IoT big data invalid information filtering method
[60]	Evaluation of system performance in steady state and under dynamical state	Proactive Cascade Prediction	IEEE Transactions on Industrial Electronics	Proactive Blackout Prediction Model, SVM

Representative SG studies report regression loss estimation, optimal dispatch, real time risk assessment, power quality event classification, false data filtering, proactive cascading failure prediction, and short term LF [61]; [57]; [63].

Extreme learning machine

Extreme learning machine (ELM) is a type of ANN that is used widely in SG research. Fast training and high generalization are reported, and real time use is therefore supported. ELM is applied to LF, energy optimization, fault diagnosis, and grid stability assessment. The output of the ELM method is shown in Equation (4) [64].

$$f_L(x) = \sum_{i=1}^L \beta_i g_i(x) = \sum_{i=1}^L \beta_i g(\omega_i \cdot x_j + b_i), \quad j = 1, \dots, N \quad (4)$$

Here, L is the number of hidden units, N is the number of training samples, β is the hidden to output weight vector, ω is the input to hidden weight vector, g is the activation function, b is the bias vector, and x is the input vector. A basic ELM structure is shown in Figure 6.

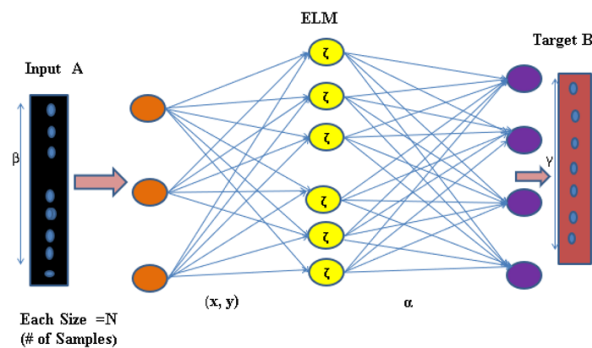


Figure 6: Basic depiction of ELM structure.

ELM based classification, kernel ELM with autoencoder (AE), feedforward neural network replacement, thermal comfort prediction, solar radiation prediction, theoretical progress, and hidden node learning are reported in the literature [65]; [66]; [67]; [68]; [69]; [70]; [71].

Table 3: Novel work based on ELM-based method in SG.

Ref.	Contribution	Application	Source	ELM-based methods
[72]	Detecting accuracy and the impact of attack intensity and environmental noise on the performance of the SG	FDI attack	CSEE Journal of Power and Energy Systems	Variational Mode Decomposition, OS-ELM
[73]	Proposing a GA-based ELM for cyber-physical system stability forecast	Stability prediction	Electric Power Systems Resiliency: Modelling, Opportunity, and Challenges	Hessenberg Decomposition ELM, GA-based ELM
[74]	Improves the accuracy, detection rate, and precision of intrusion detection and reduces the false positive rate.	Intrusion detection	Energies	Online sequential-ELM, GA-ELM
[75]	Short-term electricity price forecasting and classification of some prespecified price thresholds.	Price forecasting	Neural Computing and Applications	Multikernel-ELM, Vaporization precipitation-based water cycle algorithm
[76]	Ensuring efficient load scheduling and price reduction.	Electric load and price forecasting	Energies	Enhanced Logistic Regression, Enhanced Recurrent Extreme Learning Machine
[72]	Detecting accuracy, the impact of attack intensity, limiting environmental noise	FDI and attack detection	CSEE Journal of Power and Energy Systems	Variational Mode Decomposition, OS-ELM
[77]	Detection of false data to improve the resilience of the system.	FDI	IEEE Access	ELM-based One-Class-One-Network framework
[78]	Detecting the attack in advanced metering infrastructure	Intrusion detection	PLoS ONE	Online sequence-ELM
[79]	Detecting the FDI attack	FDI	International Journal of Electrical Power and Energy Systems	Artificial bee colony optimization, Differential evolution algorithm
[80]	Reducing the network training time and improving the generalization capability	Real-time voltage stability monitoring	Journal of Electrical Engineering and Technology	Mutual information-based feature selection

The above SG studies report ELM use in weak FDI detection, cyber physical stability prediction, intrusion detection, short term electricity price prediction, scalable LF, data recovery, advanced metering intrusion detection, FDI detection, and real time voltage stability monitoring.

Decision Trees

Decision tree (DT) models are used widely in SG studies because simplicity, interpretability, and mixed data handling are provided. DT models are applied to LF, fault detection, and energy management. Grid reliability and operational efficiency are therefore improved. Entropy for classification and mean square error for regression are shown in Equations (5) and (6) [81].

$$-\sum_{i=1}^c f_i \log(f_i) \quad (5)$$

$$\frac{1}{N} \sum_{i=1}^N (y_i - \mu)^2 \quad (6)$$

Here, f_i is the label frequency at a node, c is the number of labels, y_i is the label of an instance, N is the number of instances, and μ is the mean. Figure 7 shows the DT structure.

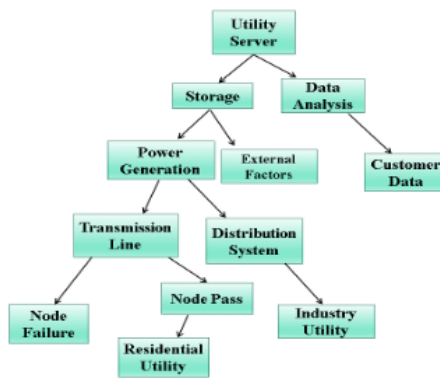


Figure 7: DT architecture used for SG purposes.

DT theory, classification and regression tree (CART) related studies, boosting evaluation, hybrid wavelet DT design, and transient security assessment are discussed in prior work [82]; [83]; [84]; [85]; [86]; [87].

Table 4: Novel work based on DT-based method in SG

Ref.	Contribution	Application	Source	DT-based method
[88]	Classification of the interarea oscillations through data measured in the generation buses	Stability analysis	Electric Power Systems Research	Decentralized DT-based approach
[89]	Detecting non-technical loss	ET detection	SCIoT 2020	DT, RF, and gradient-boosting methods
[90]	Managing thermostatically controllable loads at SGs	Frequency control	International Journal of Electrical Power and Energy Systems	DT
[91]	Ensuring energy management, increased reliability, and security	Intrusion Detection	IEEE Access	CART, Network flow extraction module
[92]	Improving the time performance and accuracy of prediction	Air-quality prediction	IEEE Access	Clustering algorithm, RNN, RF

Representative SG studies report DT use in event and attack detection, stability assessment, non technical loss detection, internet of things (IoT) security, heating, ventilation, and air conditioning (HVAC) load control, advanced metering intrusion detection, air quality prediction, remedial action design, and real time control [93]; [88].

Random Forests

Random forest (RF) is a widely used ML algorithm in SG studies because high accuracy, robustness, and strong performance with large datasets are provided. RF is applied to LF, fault diagnosis, and energy management. Demand prediction, outage prevention, and distributed energy resource optimization are therefore supported. Feature relevance in RF is defined through Equations (7) to (10) [97].

$$ni_j = w_j c_j - w_{left(j)} c_{left(j)} - w_{right(j)} c_{right(j)} \quad (7)$$

$$f_{i_i} = \frac{\sum_{j: \text{node } j \text{ splits on feature } i} ni_j}{\sum_{k \in \text{all nodes}} ni_k} \quad (8)$$

$$norm f_{i_i} = \frac{f_{i_i}}{\sum_{j \in \text{all features of } f} f_{i_j}} \quad (9)$$

$$RF f_{i_i} = \frac{\sum_{j \in \text{all trees}} norm f_{i_{ij}}}{T} \quad (10)$$

Here, ni_j is node importance, w_j is the scaled sample number at node j , c_j is node impurity, f_{i_i} is feature importance, $norm f_{i_{ij}}$ is normalized feature importance in tree j , and T is the number of trees. Figure 8 shows the RF structure.

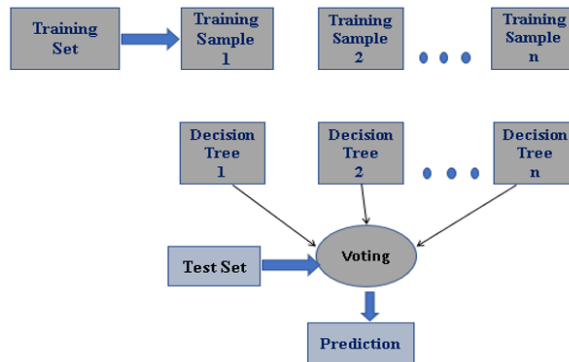


Figure 8: Basic workflow of RF algorithms.

RF applications are also reported in water resources, land surface temperature estimation, high voltage circuit breaker diagnosis, net primary production estimation, and intrusion detection [98]; [99]; [100]. The SG studies report RF use in energy management, data balancing, grid stability prediction, price optimization, energy theft detection, low carbon assessment, fault prediction, energy consumption forecasting, hidden data integrity attack detection, overload accident prediction, and human activity recognition [104]; [105].

Table 5: Novel work based on RF-based method in SG.

Ref.	Contribution	Application	Source	RF-based method
[104]	Energy management system, power factor control, and the maintenance schedule planning	Energy management	Energies	SVM, LR
[105]	Designing a model to resolve using six data balancing techniques	ET detection	Arabian Journal for Science and Engineering	Adaboost, Extra Tree, XGBoost, Light GBM, Multi-Layer Perceptron, Bagging, RF
[106]	Predicting the stability of the grid under the dynamically changing requirement of the consumer	Power consumption prediction	Expert Systems	Linear discriminant analysis, Quadratic discriminant analysis
[107]	Priority Power Scheduling	Price optimization	Production Engineering Archives	Priority Power Scheduling Algorithm, RF
[108]	Safety and reliability of the SG	FDI Attack Detection	2021 IEEE 23rd Int Conf on High-Performance Computing & Communications	Wavelet packet decomposition, RF
[109]	Achieving better predictions and better performance	Multi-class theft detection	Journal of King Saud University - Computer and Information Sciences	Bagging ensemble, RF, ANN
[110]	Checking regularly the wearable sensing device operational status of SG	Human activity Recognition	Mathematical Problems in Engineering	K-means ++ algorithm, RF
[1]	Improving energy efficiency, clean energy	Energy optimization	IOP Conference Series: Earth and Environmental Science	RF
[111]	Improving the accuracy, recall rate of the fault prediction, and the negative samples rate	Fault prediction	Enterprise Information Systems	Voted RF algorithm, NSGA algorithm
[43]	Developing fast and accurate hybrid electrical energy forecasting framework	Energy consumption forecasting	IEEE Access	Modified enhanced differential evolution, relief-F, RF
[112]	Tackling the dimensionality issue from the growth in power systems	Detection of covert data integrity assault	IEEE Transactions on Information Forensics and Security	Isolation forest (IF), RF
[113]	Preventing the over-fitting problem	LF	Computing and Informatics	Apriori algorithm, RF

Logistic Regression

Logistic regression (LR) is a statistical model that is used widely in SG studies. High suitability is reported for classification tasks in which event probability is predicted from input variables. In SGs, LR is applied to LF, fault detection, stability prediction, and energy management. The basic LR equation is shown in Equation (11) [114].

$$y = \frac{e^{(b_0+b_1x)}}{1 + e^{(b_0+b_1x)}} \quad (11)$$

Here, x is the input value, y is the predicted output, b_0 is the intercept, and b_1 is the coefficient of x . Figure 9 shows the LR structure.

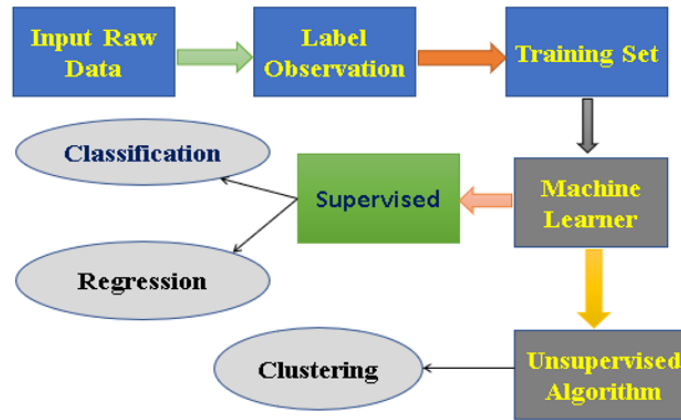


Figure 9: LR working structure.

LR use is also reported for drilling rate prediction, generalized chance modeling, risk profile construction, and ecological early warning [115]; [116]; [117].

Table 6: Novel work based on LR-based method in SG

Ref.	Contribution	Application	Source	LR-based method
[106]	Conversion of SG into a robust SG to avoid failure.	Power consumption prediction	Expert Systems	LR, DT, SVM, RF, KNN, linear discriminant analysis, quadratic discriminant analysis, Naive Bayes (NB)
[118]	Reducing the power loss	Stability prediction	International Transactions on Electrical Energy Systems	SVM, KNN, LR, DT, NN, NB
[119]	Classification of the stability of a SG	Stability	Lecture Notes in Networks and Systems	Improved Kangaroo Mob Optimization, LR
[120]	Determining optimal solutions for energy consumption, distance, and cost	Monitoring	Energies	Binary LR
[121]	Designing a low-cost solution for interconnecting electrical and electronic devices	Lightweight sustainable intelligent LF	Sustainable Computing: Informatics and Systems	KNN-regressor model, SVM
[76]	Ensuring efficient load scheduling and price reduction	Short-term electric load and price forecasting	Energies	Enhanced-LR, Enhanced Recurrent Extreme Learning Machine
[122]	Proposing a new model for forecasting, which consists of feature selection, extraction, and classification.	Load and Price Forecasting	Innovative Mobile and Internet Services in Ubiquitous Computing	Fast Correlation Based Filter, Recursive Feature Elimination, and Enhanced LR

Representative SG studies report LR use in grid stability prediction, non technical loss detection, public repository based classification, search optimization, binary classification, low cost energy estimation, and load and price forecasting [106].

1 Analysis and Discussion

ML algorithms applied in SGs are compared in terms of reliability, accuracy, and processing speed.

Reliability analysis

Figure 10 shows the reliability scores of the reviewed ML methods. Min max normalization is defined by Equation (12).

$$Y_N = \frac{f(\text{Accuracy, Precision, Recall, RMSE, Correlation Coefficient}) - Y_{min}}{Y_{max} - Y_{min}} \quad (12)$$

Here, Y_N is the normalized reliability score. Four zones are defined. Low is assigned to $0 \leq Y_N < 0.25$. Moderate is assigned to $0.25 \leq Y_N < 0.5$. High is assigned to $0.5 \leq Y_N < 0.75$. Very high is assigned to $0.75 \leq Y_N < 1.0$. ANN is identified as the most reliable model. ELM, RF, and LR are also reported with high reliability.

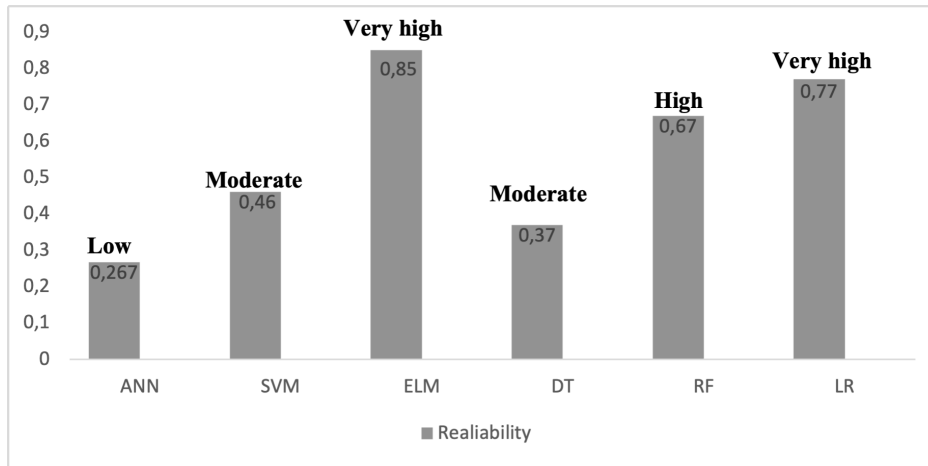


Figure 10: Reliability score of the ML-based techniques used in SG applications.

Efficiency analysis

Figure 11 presents the efficiency analysis of the reviewed ML methods. Min max normalization is defined by Equation (13).

$$X_N = \frac{\frac{\text{Absolute processing time(s)}}{\text{data samples}} - X_{min}}{X_{max} - X_{min}} \quad (13)$$

Here, X_N is the normalized processing time score. Low is assigned to $0 \leq X_N < 0.25$. Moderate is assigned to $0.25 \leq X_N < 0.5$. High is assigned to $0.5 \leq X_N < 0.75$. Very high is assigned to $0.75 \leq X_N < 1.0$. Lower score indicates faster performance. ANN is identified as the fastest model, whereas DL and hybrid or ensemble models are reported as slower. The reviewed studies are evaluated through several criteria. Figure 12 summarizes nearly 48 case studies. Accuracy, precision, and recall are shown as the most common metrics. Correlation coefficient, mean absolute error, and root mean square error (RMSE) are also used frequently. Accuracy values in SG data security vary with task type, data quality, problem complexity, and hyperparameter choice. In general, ANN and SVM are associated with higher accuracy than simpler methods such as DT and KNN. However, accuracy alone is not sufficient. Computational cost, interpretability, and generalization on unseen data are also required to be considered. Figure 13 compares reported accuracy values across the reviewed studies. In equivalent SG contexts, lower accuracy is reported for several single models, such as ANN, differential evolution (DE), and binary LR feedforward neural networks.

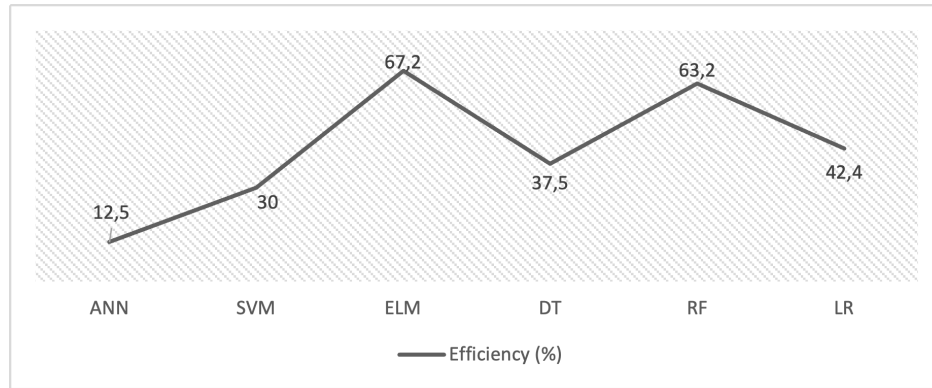


Figure 11: The score for processing speed of ML-based methods used in SG applications.

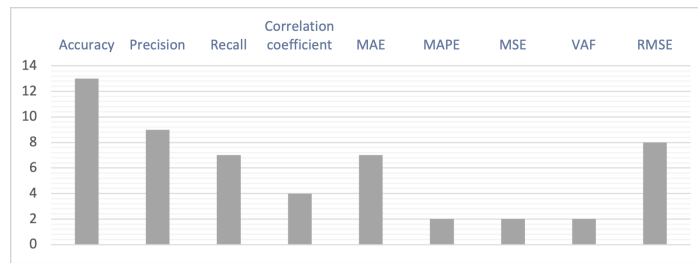


Figure 12: The distribution of evaluation metrics by frequency in the literature review.

Figure 14 summarizes the reviewed literature. Across 49 publications, 8 ANN methods, 6 SVM models, 9 ELM models, 7 DT models, 11 RF models, and 8 LR models are reported. These methods are used for security, customer incentive pricing, multi source energy management, false data detection, reactive power control, failure prediction, LF, storage management, energy management, FDI detection, islanding detection, and related tasks. ANN, ELM, and RF are identified as the most frequently used models, and hybrid ELM and RF forms are reported most often.

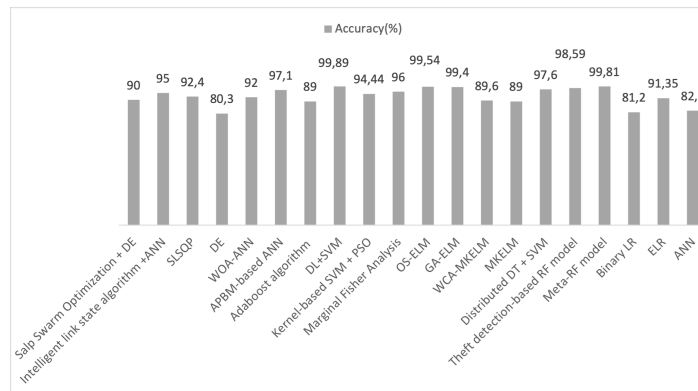


Figure 13: Comparison of the accuracy figures provided by the studies surveyed.

The number of Web of Science (WoS) publications is shown in Figure 15. The largest share is associated with ANN, long short term memory (LSTM), DT, SVM, RF, convolutional neural networks (CNNs), and LR. Single model studies dominate, but strong performance is also reported for hybrid models across several objectives. Common SG methods are summarized in Table 7. LR is simple and effective for probability based prediction. DT supports clear classification. RF improves accuracy through tree aggregation. ANN is effective for forecasting and failure prediction. SVM offers strong

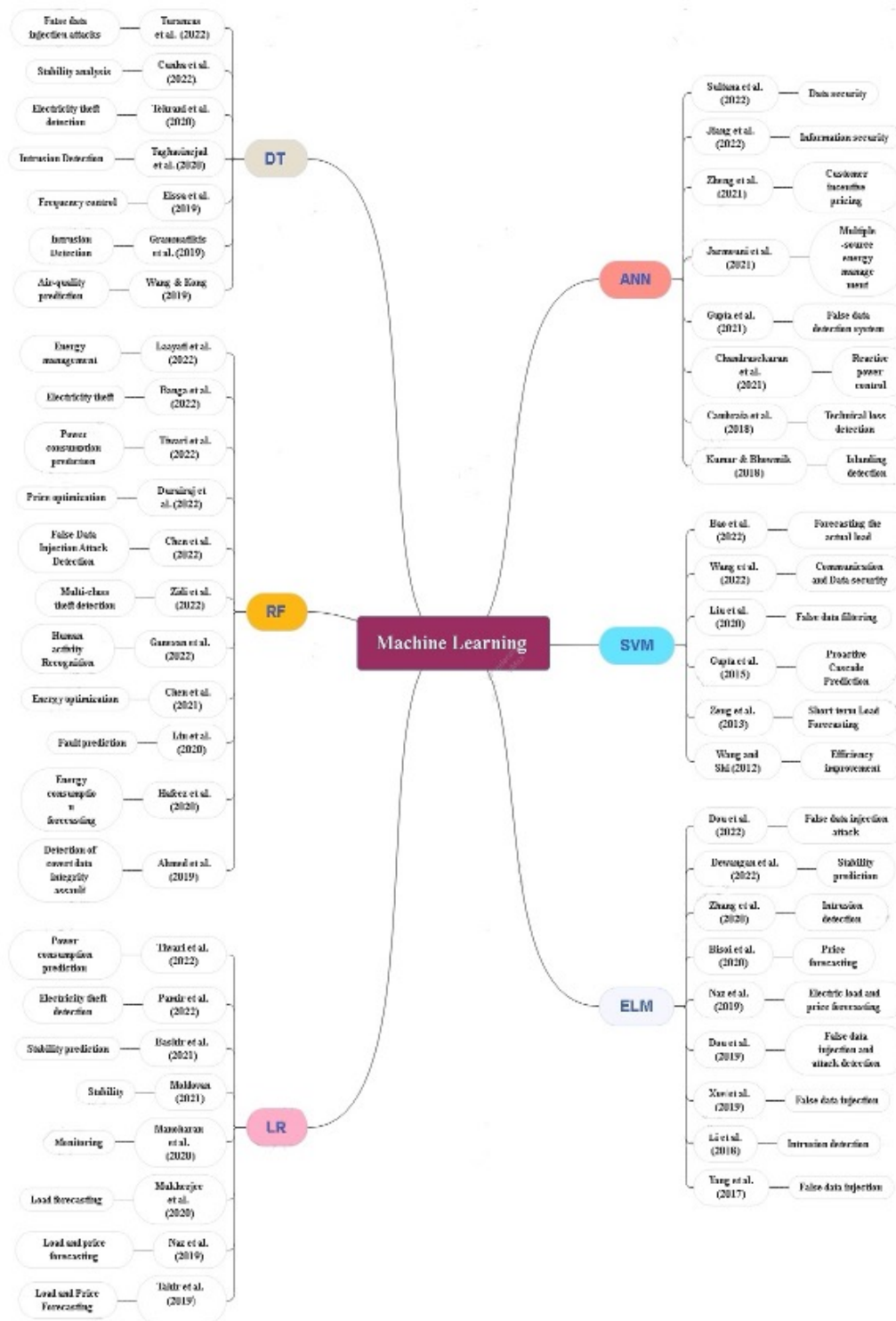


Figure 14: Taxonomy of ML methods studied for this survey in SG.

accuracy but lower speed. ELM supports fast training and real time use. Figure 16 shows the share

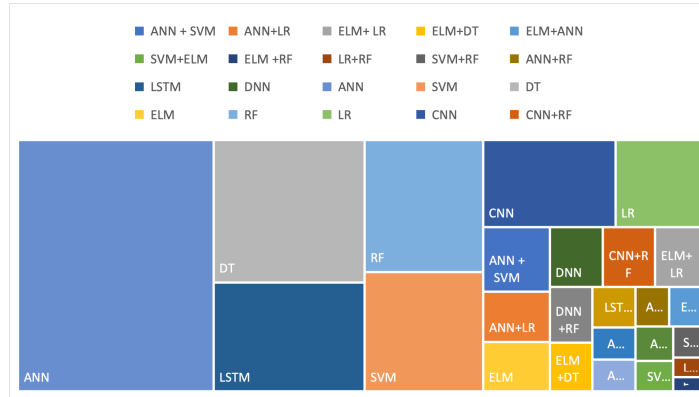


Figure 15: Notable methods of SG-related fields; the size of the rectangle is proportional to the number of publications.

of each ML method across SG application types. For security, ANN and RF are used most often. For FDI, ELM and ANN are used most often. ELM is used most often for customer incentive pricing. LR and ANN are used most often for energy management. LR is used for LF, whereas RF is suited to real time voltage stability monitoring.

Table 7: Comparison of ML models used in SG.

Method	Complication	Adaptability	Accuracy	Extracting speed
ANN	Reasonable	Reasonable	Reasonable	High
SVM	Reasonably high	Low	Reasonably high	Low
ELM	High	Reasonable	High	High
DT	Reasonably high	Low	Reasonably high	Reasonable
RF	Reasonably complex	Low	High	High
LR	High	Reasonable	High	High

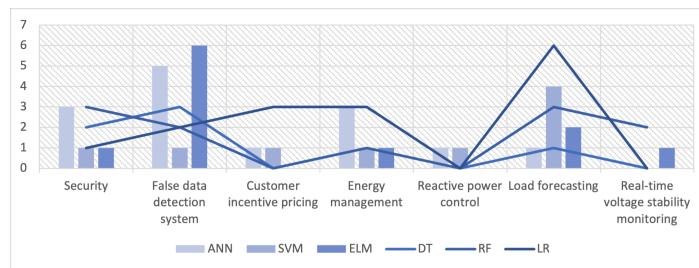


Figure 16: Share of each ML technique used in this survey across several SG application categories.

AI is identified as a major driver of SG advancement. Efficiency, reliability, and renewable integration are improved through AI, ML, and DL. Demand forecasting, renewable generation prediction, DR support, and microgrid control are strengthened. Reinforcement learning is also used for autonomous real time decisions in uncertain grid conditions. Figure 17 provides a structured taxonomy view of smart grid applications and machine learning models. It links high level areas such as energy management, load forecasting, and fault detection to specific machine learning techniques and traditional approaches. Each application is connected to relevant methods, showing how predictive maintenance, research opportunities, and power quality monitoring align with different algorithms.

The taxonomy highlights the dominant models in each area, such as convolutional neural networks and random forest, and clarifies the most common application domains, including load forecasting and energy management. This structure supports systematic comparison and evaluation of model performance, interpretability, and computational efficiency, and offers a clear guide for future research directions in smart grid intelligence.

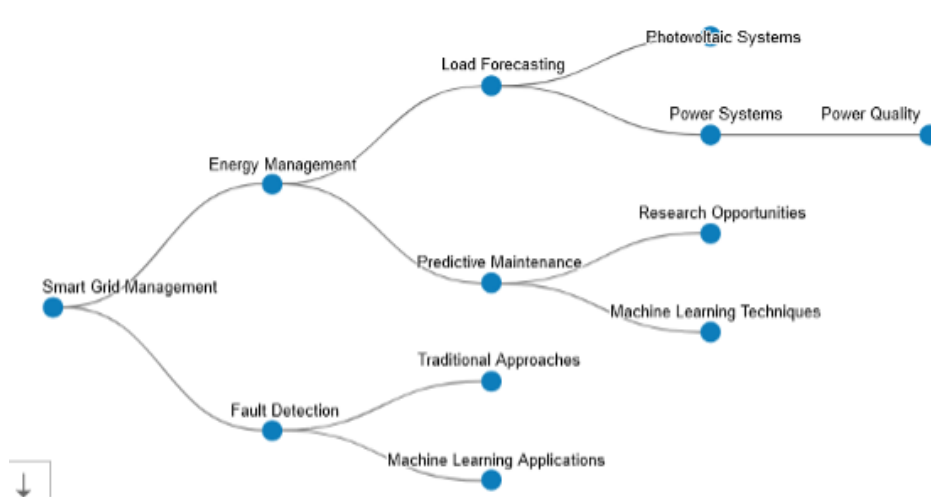


Figure 17: Taxonomy of methods with applications.

1 Conclusions

The proposed methodology is shown to be effective for resource identification and detailed review through PRISMA. A taxonomy is also provided for classification of ML models by method and domain, with comparison by accuracy, interpretability, and computational efficiency. SG use cases such as DR, energy forecasting, fault detection, and grid optimization are covered. ANN, DT, LSTM, SVM, CNNs, and RF are identified as the most widely used ML approaches in SG applications. The best performance is reported for CNN based and RF based models. LF and energy management are identified as the most common application areas. Overall, a broad view of the current state of the art is provided, and a basis for future SG research is established.

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Rituraj Rituraj
Obuda University, Budapest, Hungary.

Asanali Shayakhmetov
L.N. Gumilyov Eurasian National University,
Astana, Kazakhstan.

Viktoriya Golovachyova
Abylkas Saginov Karaganda Technical University,
Karaganda, Kazakhstan.

Amir Mosavi*
Abylkas Saginov Karaganda Technical University,
Karaganda, Kazakhstan.
Obuda University, Budapest, Hungary.
Univerzita J. Selyeho, Komarno, Slovakia.
Ludovika University of Public Service, Budapest,
Hungary.
email: amir.mosavi@nik.uni-obuda.hu

Aliya Kanatova*
Astana IT University,
Astana, Kazakhstan.

Saltanat Baipakbayeva
Faculty of Big Data and AI, Al-Farabi Kazakh National University,
Almaty, Kazakhstan.

Annamaria Varkonyi-Koczy
John von Neumann University, Kecskemet, Hungary.
J. Selye University, Komarno, Slovakia.