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Review Article

Harnessing artificial intelligence for data-driven energy predictive analytics: A systematic survey towards enhancing sustainability

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Abstract. The escalating trends in energy consumption and the associated emissions of pollutants in the past century have led to energy depletion and environmental pollution. Achieving comprehensive sustainability requires the optimization of energy efficiency and the implementation of efficient energy management strategies. Artificial intelligence (AI), a prominent machine learning paradigm, has gained significant traction in control applications and found extensive utility in various energy-related domains. The utilization of AI techniques for addressing energy-related challenges is favored due to their aptitude for handling complex and nonlinear data structures. Based on the preliminary inquiries, it has been observed that predictive analytics, prominently driven by artificial neural network (ANN) algorithms, assumes a crucial position in energy management across various sectors. This paper presents a comprehensive bibliometric analysis to gain deeper insights into the progression of AI in energy research from 2003 to 2023. AI models can be used to accurately predict energy consumption, load profiles, and resource planning, ensuring consistent performance and efficient resource utilization. This review article summarizes the existing literature on the implementation of AI in the development of energy management systems. Additionally, it explores the challenges and potential areas of research in applying ANN to energy system management. The study demonstrates that ANN can effectively address integration issues between energy and power systems, such as solar and wind forecasting, power system frequency analysis and control, and transient stability assessment. Based on the comprehensive state-of-the-art study, it can be inferred that the implementation of AI has consistently led to energy reductions exceeding 25%. Furthermore, this article discusses future research directions in this field.

Keywords: Artificial intelligence; Machine learning; Energy forecasting; Artificial Neural Network; Energy management, Predictive Analytics, Energy sustainability



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1. Introduction

Nowadays, the countries, scientists, and policymakers are paying much attention to energy sectors and the use of clean energy such as renewable energy, hydrogen, and bioenergy aiming to achieve the critical goals of decarbonization and climate change, as well as diversification of energy sources (Hoang et al., 2023a, 2023b; X. P. Nguyen et al., 2021; Pollet and Lamb, 2020). However, an emerging issue in using such energy sources is the management one. Throughout the evolution of energy management, significant attention has been directed toward investigating the application of predictive analytics (Tarasiuk et al., 2023). This recognition stems from its pivotal role in enhancing energy efficiency, integrating renewable energy sources, ensuring grid stability, enabling demand response programs, informing energy planning and policy formulation, and reducing costs for consumers (Nguyen et al., 2024; Seutche et al., 2021). Researchers leverage advanced data analytics techniques, such as pattern analysis and forecasting

models, intending to optimize energy utilization, minimize waste, and accurately predict energy demand (Alsafasfeh, 2020; Anandika et al., 2023; Sarwosri et al., 2023). This empowers businesses, industries, and households to make data-informed decisions, implement energy conservation measures, and efficiently manage energy resources (Ramirez-Sanchez et al., 2022). The integration of intermittent renewable energy sources poses challenges, and predictive analytics plays a crucial part in forecasting renewable energy generation to facilitate its seamless integration into the grid (Adhikari et al., 2024; Ugwu et al., 2022). Additionally, precise prediction of energy demand enables proactive measures for load balancing, demand response, and grid stability (Chandrasekaran et al., 2019; Wang et al., 2016). By providing valuable insights into energy patterns, researchers assist policymakers in formulating sustainable energy strategies, establishing targets for renewable energy adoption, and making informed decisions regarding infrastructure investments and energy transformation progress

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(Hoang et al., 2021; Ilham et al., 2022). Ultimately, the objective of research in energy management with predictive analytics is to establish a more resilient, dependable, and cost-effective energy system to ensure a sustainable future. The global issue of energy scarcity is increasingly severe due to the emergence of the world's oil crisis and resource shortages (Kian and Lim, 2023). In the next three decades, it is expected that the consumption of renewable energy in the world increase by 147% (Statista, 2019). Interestingly, new worldwide investments in green energy were just about ten times higher in 2019 than those in 2004. Moreover, renewable energy has grown its share of worldwide energy production to 13.4% in 2019 from 5.2% in 2007 (Statista, 2013). Speaking of all green energy sources, electricity's role has grown by a ratio of two to three than ever before, implying that every resource of the electrical system should be effectively exploited to benefit society (Lopes et al., 2007; Nguyen et al., 2022). Energy demand that varies stochastically could create a mismatch between the demand and supply of energy, which leads to the instability of the system's operation (Ullah and Baseer, 2022; Wattana and Aungyut, 2022). More interestingly, incentivization is known as a type of energy management method in which prosumers (known as the consumers that produce and use small-scale energy, so-called energy districts) are encouraged to plan their loads at specific time periods (demand-side management) (Lagouir et al., 2021; Lahlou et al., 2023). Accordingly, smart energy management is required to track and coordinate the capacities and requirements of all consumers, resources and suppliers, energy market players, infrastructure operators, as well as energy transformers (Li et al., 2023; Nižetić et al., 2023; Rowlands et al., 2011). Scientists have been studying ways to create a complete energy management model that helps not only the grid but also prosumers over the past several decades. Indeed, methods and optimization algorithms for managing energy are gradually integrated into the energy management model to provide dependable, clean, and cheap energy (Ağbulut, 2022a; Jawad et al., 2021; Li and Jayaweera, 2015). In power networks, optimization methods are used to manage the demand and supply of energy in order to meet economic load delivery, quality of service, and system reliability (Bakay and Ağbulut, 2021; Jawad et al., 2021). More significantly, an effective optimization method requires well-defined criteria, specifications, as well as system prerequisites. If there are any changes in the system specification, like changeable energy supply because of renewable sources of energy or modified requirements of prosumers, the optimization issue must be reformulated to accommodate the new parameters. In fact, important studies in the field of energy management related to prosumers and applications of smart grids have been carried out (Jadhav and Patne, 2017; Jawad et al., 2021; Li and Jayaweera, 2015; Park et al., 2016). However, significant progress is required in energy-efficient algorithms, energy management models, energy estimation, transmission, and management (Ahmed et al., 2020a; Jadhav and Patne, 2017; Kucęba et al., 2018; Park et al., 2016).

Artificial intelligence (AI) including machine learning (ML) and combined algorithms can be utilized in many fields such as energy and fuels (Drzewiecki and Guziński, 2023; Goyal et al., 2023; Sharma et al., 2023), education (Haque et al., 2024; Kim, 2024; Kim et al., 2023), communication (Hu and Qin, 2017; Melinda et al., 2024; Rumapea et al., 2024), chemical engineering (Aniza et al., 2023; Dobbelaere et al., 2021), industry manufacturing (Chau et al., 2021; Lee et al., 2018), transportation and logistics (Hu, 2018; H. P. Nguyen et al., 2023; Radonjić et al., 2020; Witkowska and Rynkiewicz, 2018; Zaki, 2024), medical (Haleem et al., 2019; Pang et al., 2023; Yunidar

and Melinda, 2023), social study (Liu et al., 2023; Triandi et al., 2023), environment (Biswas et al., 2023; Chaoraingern et al., 2023; Domachowski, 2021; Vo et al., 2021), and economy (Furman and Seamans, 2019; Suvon et al., 2023) aiming to enhance management effectiveness. For energy area, AI could be used for forecasting energy production and demand prediction (Aguilar et al., 2021; Ahmad et al., 2021; Mosavi et al., 2019), energy theft detection (Ahmad et al., 2021), demand side management (Antonopoulos et al., 2020), predictive maintenance and monitoring (H. P. Nguyen et al., 2021; Wedashwara et al., 2023), optimized energy operation (El-Shafay et al., 2023; Goswami et al., 2022), energy pricing and energy-related emission prediction (Ağbulut, 2022b; Mosavi et al., 2019), weather phenomena prediction associated with forecast (Ihsan et al., 2023; Mosavi et al., 2019), energy management and waste-to-energy management (Abdallah et al., 2020; Sharma et al., 2022a). It is noted that solar energy, wind power, hybrid energy, geothermal energy, hydrogen energy, bioenergy, biofuels, biomass, and ocean energy can all employ AI models (Ağbulut et al., 2021; Chen et al., 2021; W.-H. Chen et al., 2022b, 2022a; Jha et al., 2017; Tabanjat et al., 2018; Tuan Hoang et al., 2021). Besides, Support Vector Machines (SVMs), Artificial Neural Networks (ANNs), Ensemble, Wavelet Neural Networks (WNNs), SHapley Additive exPlanations, and Decision Trees are some examples of AI algorithms (de Ville, 2013; Le et al., 2023; Li et al., 2023; V. G. Nguyen et al., 2023; Said et al., 2022; Sharma et al., 2022b; Veza et al., 2022a; Zhang et al., 2022). Moreover, in the smart grid setting, the algorithms are extensively employed for a variety of issues including energy reliability, prediction, and management. For instance, the day-ahead consumption of energy of air conditioners in the intelligent grid was forecasted in the research mentioned in (Chou et al., 2019a) aiming to evaluate the algorithms' efficacy. Moreover, the effectiveness of a hybrid SVM as well as ANN for protective network architecture and settings was investigated to guarantee the dependability of microgrids (Ahmed et al., 2020a; Lin et al., 2019). AI techniques hold the potential to be deployed across a broad spectrum of energy control tasks. The motivation behind this work is to segregate the findings documented in this field, contextualized within the framework of autonomic computing, with the ultimate goal of achieving optimal energy control. The primary objective of this article is to critically evaluate and assess the appropriateness of utilizing AI techniques in energy management, incorporating contemporary concepts like autonomous computing to effectively organize raw data. The sub-objectives include:

- Examining the current state of AI adoption in the energy sector,
- Identifying the challenges and opportunities of using AI for energy predictive analytics,
- Discussing the potential benefits of AI for sustainability,
- Proposing a roadmap for the future adoption of AI in the energy sector.

Consequently, this research paper significantly advances our comprehension of feasible AI-driven energy management techniques. In this paper, we make the following key contributions to the field of AI for energy management:

- ✓ The paper discusses various applications of AI in energy management, including energy forecasting for demand and supply, demand response to manage energy demand, and the use of AI in managing smart grids to improve reliability, security, and efficiency.
 - ✓ The paper discusses the use of intelligent algorithms that mimic human communication, decision-making, and formal logical reasoning. It emphasizes the use of

mathematical rules based on degrees of membership and highlights the adaptability and learning capabilities of these algorithms.

- ✓ The paper explores the use of ANNs in energy management systems. It provides an overview of the structure and functioning of ANNs, including neuron representation and activation functions. It emphasizes the importance of selecting appropriate input and output variables for ANNs.
- ✓ The paper reviews the development of a forecast engine for estimating energy with heuristic and metaheuristic optimization paired with ANN. Additionally, the paper explores the influence of issue dimensions on the accuracy of the ANN model for solar power systems.

2. Research methodology

The primary objective of this literature review is to analyze the current state of the art in energy prediction and management and offer an extensive review of the extant literature. Computational prognostication plays a pivotal role in proficiently strategizing and optimizing the scheduling of the energy system. This study entails conducting a comparative analysis of diverse machine learning techniques applicable to the forecasting of time series data.

Research Query 1: What are the current and emerging applications of artificial intelligence (AI) in energy management, and how can AI algorithms be utilized to optimize energy production, consumption, and distribution to address the challenges of energy scarcity and the transition toward renewable energy sources?

Research Query 2: How can artificial neural networks (ANNs) be effectively utilized to optimize fuel economy and energy efficiency in vehicles, forecast solar power production, predict electricity demand, and optimize energy storage systems, while also improving the performance and accuracy of energy forecasting models, particularly SVM and its variants, for various applications in the energy management domain?

Research Query 3: How can hybrid energy systems benefit from the optimized implementation of predictive control methods utilizing neural networks and fuzzy logic-based energy management systems, to achieve greater energy efficiency, user comfort, and effective power flow governance while adapting to changes in system configuration?

To ensure comprehensive coverage of the relevant literature, the Scopus and Web of Science databases were searched. The outcomes of every query were organized based on their relevance and the initial 600 were subjected to manual scrutiny. Additionally, conference papers were disregarded search to concentrate on the most superior works. The search scope was confined to papers published from 2003 onwards. The literature exploration encompassed articles released between 2003 and 2024. This period was chosen to encompass the latest advancements in research while also acknowledging

foundational studies that offer a historical framework for the field. The search strategy utilized a combination of relevant keywords and Boolean operators to retrieve articles that closely align with the research queries. The keywords were selected based on their relevance to the research area and their ability to capture the key concepts and themes within the field. Each of the queries was performed separately in each of the databases in the following Table 1.

These articles underwent a systematic screening process to determine their eligibility for inclusion in the review paper. The paper selection process involved the application of predefined inclusion criteria. To be incorporated into the taxonomy, an article needed to present a machine learning (ML)-based solution that could be effectively employed for energy prediction. The selection criteria were as follows:

- The ML solution proposed must have direct applicability for the implementation of energy predictive analytics.
- Articles that merely discussed machine learning techniques in the literature review or future work section, without actually implementing a machine learning solution, were excluded from consideration.
- Review papers were intentionally omitted, although pertinent review papers are referenced in Section 1.
- Articles focusing on machine learning applications related to low-level energy management were not included in the selection process.
- The taxonomy specifically concentrates on machine learning applications for energy optimization and modeling, deliberately excluding energy policies and regulations.
- The taxonomy solely concentrates on the domains of analysis and planning, excluding considerations of demand-side management and supply-side management.

3. Artificial intelligence

Artificial Intelligence is characterized as the cognitive ability of an artificial agent to effectively traverse complex problem domains associated with a system conventionally attributed to a machine or a computational device (Bisri and Man, 2023; Luger, 2005). AI is an interdisciplinary field that integrates the paradigms of physiology and computer science wherein intelligence is conceptualized as the computational aspect of the capacity to effectively achieve objectives on a global scale (Kumar and Thakur, 2012), as shown in Fig. 1.

Intelligent algorithms encompass a logical construct that comprehends values beyond the binary concepts of true and false (Hasnaoui *et al.*, 2023). The purpose of augmenting intelligence is to emulate human capabilities for communication, rational decision-making, and application of common sense (Duraković and Halilovic, 2023). Zadeh (Zadeh, 1965) defined intelligent algorithms as a collection of mathematical rules for representing knowledge determined

Table 1Search Overy Formulation

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Query	Search keyword	Scopus	ScienceDirect	IEEE Xplore
Q1	"Energy" AND "Learning"	4890	2990	489
Q2	"Residential Energy" AND "Learning"	887	686	103
Q3	"Smart meter" AND "Artificial Neural Network"	591	340	87
Q4	"Transport" AND "Artificial Neural Network"	520	119	96
Q5	"Construction" AND "Artificial Neural Network"	479	98	79

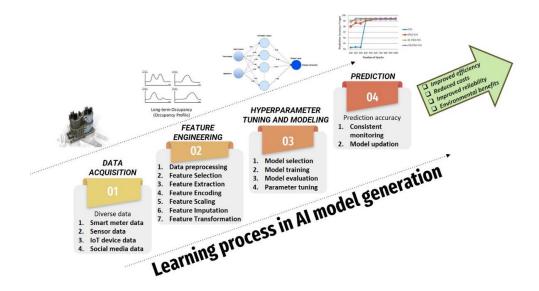


Fig. 1. Generalized learning process of artificial intelligence

based on the degrees of membership rather than the crisp membership in traditional binary logic (Natsheh, 2013). Intelligent algorithms can also be characterized as the computational process that autonomously generates the optimal results in response to varying inputs. Additionally, multiple smart programs collaborating can provide the AI with its adaptive capabilities. More remarkably, unlike a fixed mathematical formula, several of these algorithms depend on training and they could be updated to enhance their performance, whereas others can modify their actions depending on outputs and inputs, hence making them more broadly useful. This study presents a comprehensive depiction of the predominant intelligent models or algorithms that have been extensively utilized. The findings are derived from an extensive analysis of the academic literature, encompassing 581 scholarly articles published within the period spanning from 2017 to 2022. The research proceeded by selecting the most representative and recent algorithms in the state-of-the-art literature. Fuzzy logic (FL) and neural networks (NN) appear to

be the most common methods. As shown in Fig. 2, a taxonomy of artificial intelligence (AI) for energy management is depicted.

3.1. Artificial neural network for Energy Management and Forecasting

It is noticeable that a multiprocessor processing system is a type of artificial neural network (ANN), and this system is made up of a series of very basic and highly linked processors known as neurons, which are similar to biological neurons in the human brain (Rangkuti *et al.*, 2023; Razak Kaladgi *et al.*, 2021). The flowchart illustrating the process of ANN development for testing and training is depicted in Fig. 3.

In addition, Fig. 4a illustrates the fundamental model of a solitary neuron. The bias b has an impact on the activation function f by shifting it to the left or right, based on whether it is negative or positive. More interestingly, a collection of activation functions can be used to select the activation function f (as a sigmoid function, hard limit function, and piecewise-linear

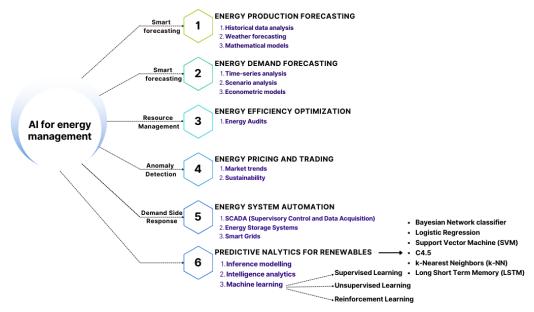


Fig. 2. Survey taxonomy

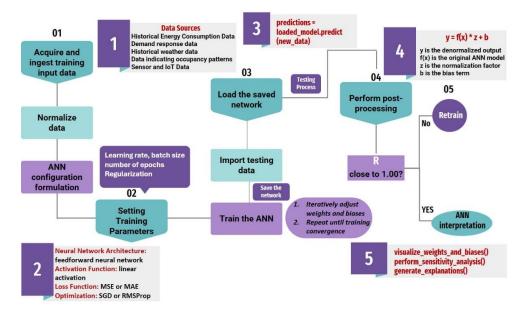


Fig. 3. Workflow for Development, Testing, and Training of ANNs

function). Also, Fig. 4b depicted some of the most common activation functions (Natsheh, 2013). Researchers have also investigated ANNs aiming to build energy management systems. In general, choosing output and input variables for an ANN has a large impact on the performance and the utilization or generalization of the network (Al Sasongko et al., 2022; Rudzki et al., 2022; Zheng Chen et al., 2014). It is noticed that the ECMS, an instantaneous optimization algorithms' representative, is considered the most potential online EMS and is currently widely applied in the real world (Kommuri et al., 2020; Wang and Huang, 2020). The process of converting fuel to electricity is carried out by adding an equivalent factor (or EF for short) which calculates the electrical energy cost as a fuel consumption's equivalent quantity. Hence, to achieve optimum energy savings, it is suggested that the EF should be a variable number that is dynamically tuned based on real-time powertrain activities. As a result, several EF estimates approaches have been developed to adaptively control EF while taking into account the vehicle state and driving circumstances. In the case of HEV applications, it is assumed that the equivalent factor is adjusted based on factors relating to the battery state of charge (SOC) at each instant, to prevent excessive SOC variation from the intended constant. More remarkably, to assure the vehicle's charge-sustaining capability, a tangent-shape function of the SOC deviation, for example, was used to rectify the EF (Tian et al., 2019). In addition, planning the SOC reference trajectory could be enhanced by including more factors on top of the travel distance (e.g. expected demand for power or future average speed) (Tian et al., 2018). Furthermore, ANNs including neurofuzzy systems and recurrent neural networks (RNN) can be utilized to produce the SOC reference trajectory depending on driving data (Han et al., 2020; Montazeri-Gh and Pourbafarani, 2017). Besides, the SOC reference generator promoted by NN makes use of NN's exceptional learning capabilities, allowing full utilization of implicit information from optimum SOC reference trajectories of distinct driving cycles. To get rid of the twofold faults that cause sub-optimum performance, the EF online estimating technique should intelligently manage the EF with no assistance of the SOC reference trajectory, while also ensuring that the SOC could end at the target value and the optimum fuel economy. Indeed, the ideal scenario mentioned above can be realized by utilizing the NN-improved equivalent consumption

minimum strategy (ECMS) driven by data. In an experiment of Xie et al. (Xie et al., 2018), an equivalent consumption minimal technique driven by data, employing an ANN to compute the equivalent factor was described. Accordingly, the NN was trained with the use of speed profiles in the real world. Based on the results, the suggested data-driven equivalent consumption technique outperformed global optimization approaches such as Pontryagin's minimal principle and dynamic programming approaches in terms of fuel economy. Apart from that, the computing time of the suggested technique in comparison to the total journey duration suggested a high potential for developing a time-conscious energy control technique. Also, the obtained findings indicated that the suggested equivalent consumption minimal method using ANN created the same fuel economy as global optimization approaches like the PMP and DP techniques, and it considerably lowered total energy consumption expense by 24.9%, 17.7%, 29.6%, and 28.7%, for initial SOC levels of 0.65, 0.85, 0.35, and 0.45, in turn in comparison with the chargesustaining and charge-depleting (CD-CS) approach based on rules (Xie et al., 2018).

3.1.1. Neural networks for energy optimization: Distributed energy resources

Apart from that, Chen et al. [54] presented a novel intelligent technique that uses dual neural networks (NNs) to adaptively adjust the equivalent factor to achieve near-optimum fuel economy. The technique does not require the charge reference state, and it uses a Bayesian regularization NN to forecast the near-optimum equivalent factor online, while a backpropagation NN is used to predict the on/off state of the engine to improve the forecast quality. Fig. 4c summarizes the design process sketch and detailed ECMS architecture based on NN. According to the results of the control performance validation and testing, the suggested NN-based ECMS was observed to create equivalent fuel efficiency to the DP optimum solution. Besides, the suggested technique achieved an average fuel savings of 96.82% of worldwide optimization outcomes overall validating driving cycles. Moreover, under WVUSUB_7 and CQ2_3, the proposed approach was projected to save 95.96% and 98.69%

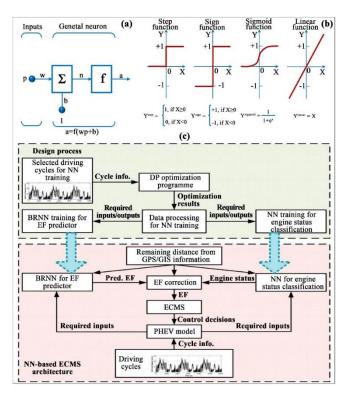


Fig. 4. (a) - ANN structure; (b) - Activation functions used in ANN (Natsheh, 2013); (c) - Framework of ANN-ECMS (Z. Chen et al., 2022)

of gasoline in turn during driving cycles that have not been subjected to NN training (Z. Chen et al., 2022).

In an alternative illustration, the estimation of projected power generation significantly influences the availability of excess energy for storage or commercialization, in addition to the potential insufficiency of energy requiring supplementation from the system. However, solar power generation exhibits sporadic patterns, rendering continual and precise prediction a laborious task. Consequently, this challenge serves as a driving force for researchers to explore the applications of NNs in energy forecasting. Additionally, the synergistic fusion of neural networks (NNs) with complementary algorithms represents an effective approach for enhancing predictive capabilities. By seamlessly combining the strengths and unique features of different algorithms, it is possible to enhance predictive performance and achieve more accurate and robust forecasts. This integration holds significant potential in optimizing predictions across diverse domains, ranging from energy forecasting to weather prediction, and opens up exciting possibilities for advancing the field of predictive analytics (Liu et al., 2017) and autoregressive moving average model (ARIMA) (Duan et al., 2021). More notably, an innovative technique was provided by Kevin et al. (Förderer et al., 2018) aiming to represent and communicate distributed energy resources' energy flexibility. In their experiment, the devices were combined with ANNs, operating as surrogate models. Moreover, the flexibility that was represented by an ANN could be determined by the state of the related devices and their surroundings, requiring just a little status update to be sent for a third party to design feasible load profiles. As a result, unlike other techniques, including support vector data description, novel ANNs were only required when there was a change in the device configuration (Förderer et al., 2018). In general, ANN could also be used to predict solar panel energy output (Eseye et al., 2018), electricity demand (Chiñas-Palacios et al., 2021a; M. Kim et al., 2019), and wind speed (T. Liu et al., 2018).

It is not hard to see that one of the primary reasons for

lowering the consumption of energy is the rise in power demand. Smys et al. (S et al., 2020) attempted to reduce the energy utilization of the street light system because of its inefficiency in managing and handling the power flow and considering current demands on the light intensity. Thus, the authors proposed a way of managing power to efficiently limit its consumption through the comparison between the light intensity and the weather conditions. In the suggested technique, ANNs were employed to govern the power of streetlights. Assessing the strategy produced findings resulting in improved power management and lower power use in street lighting (S et al., 2020). Husevin et al. (Yavasoglu et al., 2020a) discovered that the power split in HESS could be improved by developing a convex optimization issue to achieve specific objectives, leading to a 5-year battery lifespan extension. However, due to the complexity and numerous variables involved, achieving convex optimization of complex systems can be challenging, and linearization is not suitable for all systems. Therefore, to address the challenge of multi-target energy management, an approach based on neural networks (NN) was devised and trained using outputs from convex optimization. The results from simulations demonstrated that the trained NN model successfully addressed the optimization problem in 92.5% of the cases where convex optimization was employed. (Yavasoglu et al., 2020a). Significantly, Yadav et al. (Yadav et al., 2015) compared various ANN models, including GRNN (known as generalized regression neural network), nftool (so-called fitting tool), and RBFNN (radial basis function neural network), aiming to estimate the potential of solar power sources in India. Accordingly, the n-ftool was recognized for its ability to accurately estimate the target parameter in a variety of positions. Moreover, a forecast engine was created by Abedinia et al. (Abedinia et al., 2018) for estimating solar energy, based on a metaheuristic optimizer which is known as shark smell optimization paired with ANN. The researchers proposed this tool as it outperforms traditional predictors such as conventional GRNN, RBFNN, ANN, and their wavelet types

(normalized root mean square errors (RMSEs). In addition, Yaci *et al.* (Yaïci *et al.*, 2017) illustrated the ANN efficacy in modeling solar power systems, and the influence of issue dimension

(namely the number of inputs) on the accuracy. After the model was investigated with real-world data, it was concluded that accuracy decreased progressively as the size was reduced

Table 2 Features and gaps of	Table 2 Features and gaps of the considered state-of-art approaches			
Ref	Technique	Model	Performance Metrics	Identified Research Gaps
(Ahmed <i>et al.</i> , 2020b)	Adaptable energy management model	Machine Learning + Gaussian Process Regression	Prosumer Energy Surplus, Prosumer Energy Cost, Grid revenue	Model fails to consider the ramifications of uncertainty and demand response, while also neglecting to ensure the security and privacy of the data acquired.
(Chou <i>et al.</i> , 2019b)	Hybrid: Linear autoregressive integrated moving average model and nonlinear nature-inspired metaheuristic optimization-based prediction model	Autoregressive integrated moving average + Metaheuristic Firefly Algorithm	Root mean square error, correlation coefficient, mean absolute error, total error rate	The effects of data sparsity on the efficacy of machine learning models, and the influence of model selection on their performance, have not been focussed.
(Yacim and Boshoff, 2020)	Rule-based adaptive protection scheme	Artificial neural network + support vector machine	Accuracy, Correlation measurement	Utilizing a limited dataset for model training gives rise to overfitting. The consideration of spatial and temporal autocorrelation effects on property valuation models has been omitted
(Han <i>et al.</i> , 2022)	Adaptive equivalent consumption minimization strategy	RNN with LSTM trained offline	Precision, Q _{oss}	There exists an absence of insight into the variations in the effectiveness of the LSTM model contingent upon the chosen domain adaptation strategy
(Han <i>et al.</i> , 2022)	Improving the forecasting accuracy of wind speed with strong nonlinearity and nonstationarity	osition techniq error decon thods	Accuracy	The paper neglects to address the ramifications of diverse operating conditions on the overall performance of the method.
(J. Kim <i>et al.</i> , 2019)	Hybrid power demand forecasting model	(c, I)-Long Short-Term Memory (LSTM) + Convolution Neural Network	Accuracy, Kappa statistics	
(Chiñas-Palacios <i>et al.</i> , 2021b)	Energy demand variations	ANN-based model hybridized with a Particle Swarm Optimization	Prediction accuracy	This work has a limitation on performance degradation when the dimensionality of the parameter space increases.
(H. Liu <i>et al.</i> , 2018)	Short-term wind speed forecasting	Ensemble Empirical Mode Decomposition (EEMD) + Support Vector Machine (SVM)	Forecasting accuracy and management tool	Computationally expensive method
(Yavasoglu <i>et al.</i> , 2020b)	Multi-objective energy management with complex utilization of multiple energy storage units	Neural network (NN)-based machine learning	92.5% convex optimization	The sensitivity of the Neural Network on the choice of hyperparameters has not been focussed.
(Jiang <i>et al.</i> , 2020)	Effective forecasting model for nonlinear and nonstationary solar power time series	Neural network + metaheuristic algorithm	Forecast precision	The study does not encompass the impact of hyperparameter selection on the performance of neural networks.
(Al Sumarmad <i>et</i> al., 2022)	Power flow between renewable energy sources, storage systems, and their backup	ANN controllers	State Of Charge	Computationally expensive method

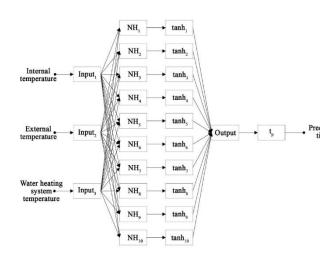


Fig. 5. Diagram of implemented neural network applied to building energy management systems (Macarulla et al., 2017)

(Moayedi and Mosavi, 2021). In general, features and gaps of the considered state-of-art approaches are given in Table 2.

According to the majority of the research, buildings in affluent nations contribute 20-40% of the world's energy consumption (Pérez-Lombard et al., 2008). Buildings utilize energy throughout their life cycle; however, 80-90% of that energy is spent during the operating period (Atmaca and Atmaca, 2015; Praseeda et al., 2016; Ramesh et al., 2010; Whitehead et al., 2015). As a result, building energy management systems (BEMS) plays a critical part in this sector (Doukas et al., 2007). Indeed, BEMS has contributed to continuously managing the energy of the building (Doukas et al., 2007), making buildings smarter through real-time automated control and monitoring (Xiao and Fan, 2014), as well as optimizing energy consumption (Gangolells et al., 2016). Therefore, Marcel et al. (Macarulla et al., 2017) outlined the approach for the implementation of a predictive control method in a commercial BEMS applied in boilers in buildings, and the obtained results were also described. The suggested control is according to a NN which starts the boiler daily at the optimal moment, depending on the surrounding environment, intending to attain thermal comfort levels when a working day begins. In particular, the training patterns were created using testing data collected from two heating seasons. After that, a variety of NN structures were examined and the optimal one was utilized to build and apply the predictive control approach in the current BEMS. Ultimately, a set of KPIs was employed to evaluate the effectiveness of the control plan. The block diagram of the NN implemented in the BEMS was illustrated in Fig. 5. Apart from that, the Tw, Te, and Ti values were normalized using input boxes. The control method was evaluated for one heating season, and the advantages of the suggested control technique were assessed using a set of primary performance parameters. According to the findings, predictive control being utilized in a BEMS for boilers in the building could lower the energy needed for heating the building by roughly 20% while maintaining comfort for the users (Macarulla et al., 2017).

3.2. Fuzzy logic for energy management through intelligent systems in hybrid energy and microgrid systems

It is obvious that the exploitation of renewable sources of energy has enormous promise for various applications, and offgrid stand-alone systems particularly bring several advantages. The entire system is known as a HES (hybrid energy system) since it combines at least one renewable resource with one extra resource and one storage factor. Additionally, a proper EMS must be created to govern the power flow among the parts of a HES. The EMS is often a centralized controller which controls all of the components. As a result, the hybridization level of the HES increases the complication of building an EMS. Furthermore, if there is any change in the configuration of HES, such as when one component withdraws due to a defect or maintenance, the central controller is incapable of adjusting its reaction. Apart from that, in case a new factor is introduced to an EMS with a central controller, it is necessary to modify the EMS. Thus, it is intriguing to determine a dependable, flexible, scalable, and open EMS. More noticeably, a novel method for HES based on multiagent system technology (MAS) was developed by Jérémy et al. (Lagorse et al., 2009), in which HES was viewed as a collection of autonomous entities that collaborated rather than a global system to govern. According to the above-mentioned key characteristics, intelligent element and MASs technology is predicted to fundamentally transform how complicated, open, and distributed systems are designed and deployed. Because of the dispersed, open, and complicated features of HES, MAS technology seems to be a suitable answer for energy management in HES. Additionally, an HES may be considered a collection of "intelligent" and autonomous factors that can adapt to situations in their environment using an agentbased method (Lagorse et al., 2009). Roiné et al. (Roiné et al., 2014) described an EMS in which the FLC analyses the evolution of pricing over a single day, the production, the demand for energy, and the time of day to provide an economical grid. Besides, scenarios with more degrees of freedom were also taken into account in other works, in which the EMS governs distinct storage factors, controllable, or even a combination of both factors mentioned above aiming to conduct demand side management and DR approaches (Pascual et al., 2014; Tascikaraoglu et al., 2014; Wang et al., 2014). In this scenario, the control systems utilized are often complex, such as MPC (Model Predictive Control), and encompass both production and demand prediction (Prodan and Zio, 2014)(Bruni et al., 2015). Barricarte et al. (Barricarte et al., 2011) proposed an EMS design based on heuristic knowledge of the wanted micro-grid behavior, in which the amount of power attributed to the storage system and the grid is calculated using adjustable analytical expressions related to the power balance between production and consumption, along with the battery SOC serving as major variables. The aforementioned heuristic knowledge suggested employing FLC to build the EMS for the instance under investigation, because this technique readily incorporates the user's experience instead of utilizing a system's mathematical model (Fossati et al., 2015; Mohamed and Mohammed, 2013; Passino et al., 1998). Furthermore, using the identical input variables (Barricarte et al., 2011), the researchers showed that the FLC creation with only 25 rules moderately enhanced battery SOC as well as the grid power profile achieved in (Aviles et al., 2012)(Barricarte et al., 2011)(Arcos-Aviles et al., 2018). More importantly, Diego et al. (Arcos-Aviles et al., 2018) designed a minimal complexity FLC with just 25 rules to be incorporated in an energy management system, applied in a home grid-connected micro-grid with renewable sources of energy and storage ability. The major purpose of this design is in order to retain the battery state of charge in safe limits while minimizing the fluctuations of the grid power profile. It is noted that rather than relying on predictions, the suggested methodology employed not only the battery state of charge but also the microgrid energy rate of change for

raising, reducing, or maintaining the power absorbed or delivered by the mains.

3.2.1. Comparative analysis of microgrid energy management Strategies

Bogaraj et al. (Bogaraj and Kanakaraj, 2016) showed an energy management system for microgrid systems based on intelligent multi-agent systems. This system maintains the balance of power between sources of energy and loads by utilizing forecasts of PV production, load demand, and wind production to provide the needed load. In addition, another MAS was presented by (Aung et al., 2010), applied in a microgrid system aiming to obtain optimal dispersed source utilization with the highest level of output from renewable sources and the lowest diesel use. Furthermore, Boudoudouh et al. suggested a multi-agent system for microgrid energy management, described in (Boudoudouh and Maâroufi, 2018). The simulations were carried out with the help of Java Agent Development and MATLAB-Simulink tools. This model's dependability was proven by meeting needs like autonomy and adaptability in a way that any modifications would not break the entire control method system. Aside from that, Logenthiran et al. (Logenthiran et al., 2012) studied a multi-agent system towards the microgrid's real-time operation, proposing an operational approach concentrated on production scheduling and demand-side control. The research described above also highlighted the usefulness of multi-agent systems when applied in microgrids. Notably, in this study, the MAS technique was employed to create an energy control system for microgrid systems that is based on the maximizing of renewable resources, and the bidirectional DC or DC converter was handled by ANN controllers. Besides, Aiman et al. (Albarakati et al., 2021) suggested an EMS based on maximizing energy exploitation from renewable sources by operating them in Maximum Power Point Tracking conditions. Furthermore, the stored energy was managed by applying ANN controllers to optimize battery discharging and charging. The primary goal of this system is so as to retain the balance of power in the microgrid as well as to give a flexible and configurable control for various situations with all variation types (Albarakati et al.,

In fact, because of the intermittent and stochastic character of deeply penetrated renewable sources of energy and demand, efficient multi-energy management in a microgrid is considered a difficult issue. Thus, to tackle this hindrance, it is necessary for the energy management system to frequently employ day-ahead energy planning based on prediction and real-time energy distribution for successfully coordinating the

operation of dispatchable elements, such as thermal units and energy storage based on battery. Also, an adaptive optimum energy management solution based on fuzzy logic was provided by Dong et al. (Dong et al., 2021) for adaptively developing suitable future fuzzy rules for dispatching energy in real-time in the context of operational uncertainty. It is noted that real-time energy distribution depending on optimum fuzzy logic rules established may then be conducted to fulfill different operational objectives, such as minimum cost of operation and lowest power fluctuation. The suggested technique was thoroughly tested in simulation trials against two current methods, including the dispatch technique based on online rule and the offline scheduling approach based on meta-heuristic optimization (Dong and Sharma, 2023). According to the numerical findings, the presented energy management approach was proved to outperform others (Dong et al., 2021). More remarkably, Deepak et al. (Jain et al., 2022) created energy management based on fuzzy logic and FLEM-TFP for smart transport systems using Cyber-Physical Systems. The presented FLEM-TFP system consists of two major processes, including Traffic Flow forecast and energy management. More interestingly, the engine torque required is also computed using an ANFIS (known as adaptive neuro-fuzzy inference system) model based on a variety of measurements. Furthermore, in intelligent transportation systems, an SFO-based FWNN technique is utilized to predict traffic flow. The trials revealed that ANFIS-FFA has brought good results, with an average TFC obtained being 25.98, which is significantly lower than the values achieved by the other approaches. In addition, it is clear to see from afore-mentioned data that the proposed method could increase not only energy efficacy but also total fuel economy. In the future, the provided model might be used to create methods for providing dynamic resources in an intelligent transport systems environment for Cyber-Physical Systems (Jain et al., 2022). The tabulation of **Table 3** presents a comprehensive comparative analysis of the features examined by the prior scholarly review articles.

3.3. Support vector machine (SVM) in energy regulation

Support vector machine (SVM) has been employed as an artificial intelligence model and is a well-known supervised machine learning approach to classify (Novitasari *et al.*, 2023)(Kusnawi *et al.*, 2023). Also, it is applicable to not only classification but also regression difficulties. Indeed, the core idea of SVM is to transfer input characteristics to a higher-dimensional plane (Karaağaç *et al.*, 2021). More notably, the kernel function simplifies the learning process by transferring non-separable data in input data space to data that can be

Table 3
Comparative analysis of intelligent anargy prediction guyyaya

Literature	Energy efficiency	Energy demand prediction	Data-Driven methodologies	Energy modeling	Control mechanisms	Energy management
(Khan et al., 2020)	X	-	-		-	-
(Tabanjat <i>et al.</i> , 2018)	-	-	-	-	-	Х
(Tascikaraoglu <i>et al.</i> , 2014)	-	X	X	-	-	X
(Pascual et al., 2014)	-	X	-	_	X	X
(Prodan and Zio, 2014)		X	X	X	X	Х
(Bruni <i>et al.</i> , 2015)	-	X	-	-	X	X
(Paudel <i>et al</i> ., 2017)	X	-	X	X	-	-
(Zendehboudi et al., 2018)	-	X	-	X	-	-
(Sameti <i>et al.</i> , 2017)	-	-	X	-	-	-
(Houssein, 2019)	-	-	X	X	-	-
(Runge and Zmeureanu, 2019)	X	-	-	X	-	Х
(Elsheikh <i>et al.</i> , 2019)	-	-	-	x	-	X
This review strategy	X	X	X	X	X	Х

separated in a higher dimensional one (Ağbulut *et al.*, 2020; Paudel *et al.*, 2017). Moreover, SVM is regarded as among the finest machine learning techniques for both regression and classification, according to some statistical learning theories (Gao *et al.*, 2003; Yuan *et al.*, 2010). When the results of SVM were compared to those of other strong data-driven empirical techniques like ARIMA, RBF, MLP, and IIR-LRNN, the SVR results were observed to exceed or be equivalent to those of other learning machines (Erfianto and Rahmatsyah, 2022; Moura *et al.*, 2011; Said *et al.*, 2023). Additionally, SVR is thought to function well for time series analysis because of better generalizability and the capability of ensuring a global minimum for certain training data (Fuadi *et al.*, 2021; Wu *et al.*, 2004).

For the link between the variable and the goal value, Sai et al. (Sai et al., 2020) employed an SVM with enhanced fitting and inserted the fitting forecast model into the response surface approach. Following collaborative analysis, the model was fed into a non-dominated sorting genetic algorithm-II. In addition, following the optimization operation, the optimum working conditions for enhancing the operating efficacy of the solar membrane distillation system were obtained, allowing open-pit mine prosumers to conduct smart management of producing, storing, and consuming solar energy at the same time (Sai et al., 2020). In a study by Azam et al. (Fuadi et al., 2021), electricity usage was forecasted as part of the intelligent power grid and electrification network information enhancement with the goal of performing energy management. Also, an SVM was utilized in the research to estimate electrical loads and compare the results to measurable electrical loads. In comparison with industrial, commercial, or residential electrical loads, laboratory electrical loads had unique features. Besides, RMSE was used for result prediction at various levels of trust or accuracy. The attained prediction technique had MSE = 0.14, MAE = 0.21, and RMSE = 0.37, indicating that SVM might be a useful tool for managing energy (Fuadi et al., 2021). It is noted that the microgrid dispatch's optimization is obtained by using data from renewable energy generation and load predictions in microgrids. Consequently, energy forecasting is critical in the electrical industry. Also, accurate prediction of power load is crucial for lowering the consumption of energy, decreasing power generating costs, and improving social and economic benefits (Khan et al., 2020). A number of approaches have been employed to forecast wind and solar energy supplies. In terms of predicting, the SVM modeling technique was demonstrated to have higher effectiveness compared to other modeling methods as the SVM is fast, simple to use, and gives accurate results. According to research based on significant analysis, SVM models can yield much greater accuracy in comparison with other models (Zendehboudi et al., 2018). Meanwhile, according to a study by Ehab et al. (Issa et al., 2022), SVR is a regression model utilized for optimizing. In fact, SVR is known as a form of SVM that could learn regression functions and is an SVM classification technique extension. Thus, Improving the accuracy of energy projections is necessary for the electrical grid to operate more effectively (Issa et al., 2022). More intriguing, the accuracy of SVM, a prominent machine-learning technique for simulating solar radiation was investigated and proved by Meenal and Selvakumar (Meenal and Selvakumar, 2018). When used with an ideal set of data, the strategy mentioned above showed superiority over the empirical methods and ANN for this goal. Aside from that, Quej et al. (Quej et al., 2017) researched the capabilities of SVM, ANN, and ANFIS in replicating sun radiation daily, with average correlations of 0.689, 0.652, and 0.645 respectively for the top models, so the SVM has been considered the most trustworthy predictor (Moayedi and Mosavi, 2021).

3.3.1. Comparison of SVMs and ANNs for energy forecasting

Some professionals researched assessment rules, energy regulatory system model creation, system state forecast, and the right combination of the energy regulatory system and AI (Zhu et al., 2020)(Armin Razmjoo et al., 2019). Moreover, the energy regulating system's overall performance was measured by Yan et al. (Yan et al., 2020a) with the employment of an analytic data model. The purpose of applying this model was to investigate the link between the state change of a certain energy sort and the overall regulatory state. Ultimately, the design experiment validated the method's position in studying the energy regulation system's data perception (Yan et al., 2020b). Furthermore, based on data mining, the authors suggested an enhanced SVM method. It might considerably take advantage of sensing information acquired by intelligent devices based on the rough identification of the energy supervision system's data status. Zhu (Zhu, 2021) studied the e-commerce energy regulatory system model employing data mining and the SVM technique. The experimental study demonstrated that the updated SVM technique could achieve objective regulatory efficiency assessment based on data exploitation and might result in the best method depending on scenarios in the actual application phases of the energy supervision system. Accordingly, the performance was observed to be good, suggesting that the energy supervision system could achieve above 97%, which was greater than the majority of the most recent techniques (Zhu, 2021). Low-energy buildings have been viewed as a viable alternative for the construction environment in order to meet high energy efficacy criteria. Nevertheless, in comparison to traditional buildings, low energy buildings add a significant time constant, which slows down the heat transfer rate between the building interior and the outer environment and at the same time, adjusts the inside climate albeit rapid changes in climatic circumstances. As a result, Subodh et al. (Paudel et al., 2017) emphasized an AI model to estimate the energy usage of buildings with the use of SVM. According to the numerical findings, the "relevant data" modeling strategy, depending on limited representative data selection, predicted heating energy demand more accurately (R2 = 0.98; RMSE = 3.4) compared to the "all data" modeling method (R2 = 0.93; RMSE = 7.1) (Paudel et al., 2017). In an investigation conducted by Sai et al. (Sai et al., 2020), an upgraded SVM was employed and the fitting prediction model was inserted into the response surface approach for the relation between the desired value and the variable. Interestingly, a set of optimum operating conditions for the solar membrane distillation system could be achieved after the optimization using SVM fitting as well as an NSGA-II multi-goal optimization technique. In particular, the cold-end cooling water flow was 194.14 L/h, the hot-end feed temperature was 65.76C, the membrane area was 0.03 m2 and the hot-end feed flow was 171.56 L/h. In addition, the researchers also discovered that the optimum operating conditions were gained after the operation of optimization aiming to promote the operating efficacy of the solar membrane distillation system, allowing open-pit mine consumers to smartly manage production, storage, and consumption of solar power at the same time (Sai et al., 2020). More noticeably, Kaytez et al. (Kaytez et al., 2015) examined regression analysis, SVM, and ANN forecasting accuracy for predicting the consumption of power in Turkey. It is noted that total power production, population, total number of customers, and installed capacity were utilized as inputs while total electricity consumption was employed as output, with the use of data

during the period of 1970-2009. When the findings were compared, the MAPE of the LS-SVM experiment results was 1.004%, while 1.19% was attained for the ANN, and 3.34% for the statistical regression analysis model. Besides, Ogcu and Demirel et al. (Oğcu et al., 2012) predicted power consumption in Turkey using ANN and SVM, and they spent two years creating models based on monthly energy use data. The MAPE utilized by the SVM and ANN for the test set of data was 3.3 % and 3.9 %, in turn (M. Shao et al., 2020). Indeed, there is no intrinsic approach in SVMs and NNs for specifying the states and related methods. The above-mentioned factors could account for the reason why SVMs and NNs have been preferred for energy prediction rather than energy control. Furthermore, SVMs and NNs both contain numerical parameters that could be changed, which could influence how well they function. Attempting to manually modify the settings, on the other hand, is not practical. Significantly, iterative tuning of the model might be accomplished by the employment of optimization methods, including Cuckoo Search Algorithm (T. Liu et al., 2018), Particle Swarm Optimization and Grasshopper optimization algorithm (Chiñas-Palacios et al., 2021a; Eseye et al., 2018; Veza et al., 2022b; Zhang et al., 2023), Genetic Algorithm (Sameti et al., 2017), and Dragonfly Algorithm (Li et al., 2023; Zhang et al., 2019).

3.4. Reinforcement learning and metaheuristic algorithms

Noticeably, a number of research have looked at real-time dispatch methods for energy management to deal with the effects of stochastic properties and forecast mistakes. Based on **RBC** model-free learning approaches, (Venayagamoorthy et al., 2016; Yazdanian and Mehrizi-Sani, 2014) was created for optimum management and control of the system. Interestingly, the Lyapunov optimization was employed in the online EMS with constraint relaxation in the investigations (Shi et al., 2017; Yan et al., 2019). The resolutions mentioned above frequently examine only the present operational states of the system and frequently simplify the operational requirements to facilitate real-time calculation. Hence, effective energy management is difficult to achieve over the long run. In addition, Markov decision processes (MDPs) may be in use for optimizing real-time energy dispatch. Based on the equation of Bellman for decomposing temporal dependency, DP and ADP (Zeng et al., 2019) can be employed to handle such a stochastic sequential choice issue repeatedly. Besides, RL has recently been regarded as a potential technique for solving MDPs efficiently (W. Liu et al., 2018). In another study of Zhang and Sun (Zhang and Sun, 2016), they created a consensus transfer Q-learning algorithm with the aim of energy dispatch which shared Q-value matrices and used previous information to accelerate algorithm convergence. For dynamic economic dispatch, (Dai et al., 2020) suggested an RL method in which state-action-value function approximation was integrated with multiplier distributed optimization based on splitting. Nonetheless, to prevent prohibitive computational complications because of the highdimensional state space, the aforementioned methods frequently need feature characterization and complex learning rules (Dong et al., 2021; Mnih et al., 2015). As reported, heuristics and Bayesian networks were also utilized to manage energy. Regarding heuristic algorithms, they are known as a form of algorithm based on the search that seeks the best solution to a specific issue (Desale et al., 2015). They have been utilized in the literature to optimize EV charging schedules (Vasant et al., 2020), the energy consumption of cooling systems in a building (Ikeda and Nagai, 2021), trading portfolios for electricity markets (Faia et al., 2017), and energy resource utilization in a

microgrid (Bukar *et al.*, 2022). Indeed, heuristics are valuable because they can provide potential answers to issues for which there is no obvious answer (Ali *et al.*, 2023). Moreover, some factors such as EV scheduling and the utilization of energy resources are affected by elements that are not always under control. As a result, Heuristics can present a viable solution that can be assessed. However, it might not be common since understanding the way to employ it in an energy management AI can be challenging. Whilst RL and FL algorithms instantly produce an action that can be employed immediately, heuristics search for resolutions (Li *et al.*, 2023).

Speaking of Bayesian Networks, they are graphs supporting the description of the possibilities of events happening based on the present state (Horný, 2014). In the document, Bayesian Networks have been utilized for user response prediction to demand side management measures (Z. Shao et al., 2020), for detecting prospective variations in electricity markets (Roje et al., 2017), and taking into consideration the uncertainty in energy usage and solar PV energy generation (Sun et al., 2020). It is not hard to see that Bayesian networks are valuable in managing energy because they are capable of quantifying uncertainty, as well as the production of renewable energy might be intermittent, and user schedules can alter. It is noticeable that Bayesian Networks can be unpopular since, like Heuristics, applying Bayesian Networks in an energy management AI could be difficult. The Bayesian Network provides a map of probabilities; however, how to teach an AI to assess those probabilities is such an issue (Li et al., 2023). Furthermore, metaheuristic algorithms have opened a new path for more powerful predicting models based on the skeleton of traditional tools such as ANFIS and ANN (Bakır et al., 2022). The methods mentioned above are commonly utilized for analyzing renewable energy (Corizzo et al., 2021; Houssein, 2019), such as solar energy (Bessa et al., 2015), wind power (Cavalcante et al., 2017; Liu et al., 2019), and, more specifically, solar energyrelevant simulations (Akhter et al., 2019; Elsheikh et al., 2019). More importantly, to avoid concerns such as local minima, such approaches (namely metaheuristic-based hybrids) give ideal parameters for the core prediction technique (Moayedi et al., 2019). Several researchers studied hybrid metaheuristic techniques to improve algorithm performance. Several of the above-mentioned hybrid algorithms include the many-objective optimization model (Cao et al., 2020d, 2020a, 2020b, 2020c), the whale optimization algorithm (Tu et al., 2021; Wang and Chen, 2020), moth-flame optimization (Shan et al., 2021; Wang et al., 2017; Xu et al., 2019), grey wolf optimization (Hu et al., 2021; Zhao et al., 2019), harris hawks optimization (Chen et al., 2020; Zhang et al., 2021), global numerical optimization, bacterial foraging optimization (Xu and Chen, 2014), Monarch Butterfly optimization (Bacanin et al., 2020), the grasshopper optimization algorithm (Yu et al., 2022), multiobjective 3-d topology optimization (Cao et al., 2020e), fruit fly optimization (Shen et al., 2016), topology optimization (Fu et al., 2020), the fuzzy optimization method (Chen et al., 2019; Wasista et al., 2023), and data-driven robust optimization (Moayedi and Mosavi, 2021; Qu et al., 2021).

3.4.1. Comparison of different meta-heuristic optimization algorithms

In general, energy management in smart grids has common goals such as minimizing electricity expenses, maximizing user comfort, lowering PAR, integrating renewable sources of energy, and reducing aggregated power usage. A lot of demand-side management approaches have recently been introduced to attain the aforementioned targets. Besides, non-integer linear programming, mixed integer linear programming, convex

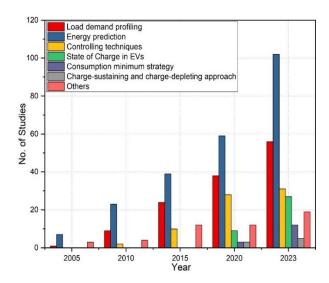


Fig. 6. Segregation of articles based on the application scenario

programming, and mixed integer non-linear programming are in use for reducing costs and energy usage (Molderink et al., 2009; Soares et al., 2011; Sousa et al., 2012; Tsui and Chan, 2012). These systems, however, cannot manage huge quantities of equipment. Hence, distinct meta-heuristic optimization strategies can be utilized for managing energy in smart meters address the shortcomings of the aforementioned methodologies. For instance, some researchers employed a genetic algorithm aiming to minimize power costs (Arabali et al., 2013; Zhuang Zhao et al., 2013). In addition, demand response as well as ant colony optimization was utilized to cut down electricity bills and the use of aggregated power (Liu et al., 2011; Tang et al., 2014). It is obvious that the majority of energy is utilized in residential areas, and it is continually increasing, which has drawn the attention of scientists to household appliance scheduling. Zafar et al. (Zafar et al., 2017) assessed the performance of a home energy management system with the use of three meta-heuristic optimization approaches: harmony search algorithm, enhanced differential evolution, and bacterial foraging optimization, to minimize electricity expenses, consumption of energy, and lower peak to average proportion while maximizing the comfort of users. The findings of their simulation revealed that there is a trade-off between the expenses and the user's comfort. Also, the findings demonstrated that the harmony search algorithm outperformed other approaches in terms of costs (Zafar et al., 2017). In another study, Galván et al. (Galván et al., 2017) took advantage of a multi-objective PSO approach to optimize the SE modeling intervals, and they also created a nonlinear technique employing ANN, and their results indicated the PSO optimizer's great applicability for the given target. In addition, two metaheuristic approaches were utilized in an experiment by Zhao et al. (Zhao et al., 2020) to forecast the compressive strength of concrete, including shuffled complex evolution and teaching and learning based on optimization. Similarly, this technique was also effectively employed by Halabi et al. (Halabi et al., 2018), in conjunction with an ANFIS system to approximate solar radiation every month. Meanwhile, Vaisakh et al. (Vaisakh and Jayabarathi, 2022) proposed a mixture of two approaches for modifying the structure of different ANNs used in SIr forecasting, namely the grey wolf optimization and the deer hunting optimization algorithm. According to the results obtained, the introduced optimizer achieved promising

enhancement. Furthermore, Louzazni et al. (Louzazni et al., 2018) demonstrated the firefly algorithm's capability aiming to assess the photovoltaic system's parameters under various scenarios. In comparison to prior utilized metaheuristic algorithms, the firefly algorithm was reported to produce more trustworthy and valid results when adjusting photovoltaic parameters. More interestingly, Bechouat et al. (Bechouat et al., 2017) proved the efficacy of the PSO and GA for the same target. Whereas, Abdalla et al. (Abdalla et al., 2019) effectively applied wind-driven optimization to the optimum power monitoring of photovoltaic systems (Moayedi and Mosavi, 2021). The major applications encompass load demand profiling, energy prediction, controlling techniques, state of charge in EVs, consumption minimum strategy, and charge-sustaining depleting approaches. The articles are classified and arranged based on these application scenarios of ANN, and an extensive comparative analysis of the features considered by these articles is presented in Fig. 6.

The target of the agent in RL is to maximize or minimize a This value might represent energy expenses or the consumption of energy in the context of energy management. An RL algorithm constantly alters its operations in response to environmental feedback. Besides, unsupervised learning (or UL for short) approaches are associated with recognizing important patterns in data and clustering them after that, based on the patterns identified above. Therefore, they are valuable in categorization difficulties. Since it is not easy to apply data clustering to energy management, unsupervised learning tends to be less common (Jo, 2021)(Li et al., 2023). Indeed, RL is a subfield of machine learning research in which an agent learns itself what behaviors to perform in a given environment to maximize the reward (Barrett and Linder, 2015). More interestingly, this is often related to a large amount of error and trial from an agent when it learns the greatest reward can be achieved from which actions. Apart from that, the algorithm is a general pseudocode that outlines the major phases of a normal RL algorithm (Mason and Grijalva, 2019). Notably, model-free and model-based RL algorithms are the two types of RL algorithms. Additionally, Dyna, Explicit-Explore-Exploit, Queue-Dyna, and Prioritized sweeping are examples of algorithms based on the model. Whereas, it is unnecessary for model-free techniques do create an environment model. Many commonly employed RL algorithms, such as SARSA and Q Learning, are known as model-free. In particular, Q Learning (Barrett and Linder, 2015) is considered among the most wellknown RL algorithms. Indeed, it is a model-free and off-policy reinforcement learning approach, in which off-policy agents learn the value of their policies independently of their actions (Barrett and Linder, 2015; Mason and Grijalva, 2019).

3.4.2. Reinforcement learning techniques for intelligent energy management

More importantly, the optimization framework depends on reinforcement learning using the Q-learning approach. This strategy motivates learning via the use of rewards or penalties based on a series of actions in response to setting dynamics (Panait and Luke, 2005; Sutton and Barto, 2018). Moreover, in a deterministic scenario, the approach can determine the most potential series of actions for a certain environment state, but in a stochastic one, it can account for the uncertainty in environment exploration (Panait and Luke, 2005). By decreasing power consumption, the Q-learning technique has been proven to obtain great performance in terms of managing the dynamic power of embedded systems (Prabha and Monie, 2007; Tan et al., 2009). Furthermore, the method has also been

used for creating a complete and advantageous demand response model for power pricing (Yousefi et al., 2011)(Mason and Grijalva, 2019). Particularly, a retail energy supplier utilizes Q-learning to establish appropriate real-time pricing while taking into account various factors like price limits and consumer replies. For intelligent energy management, the Qlearning technique can be combined with other methods, including Metropolis Criterion-based fuzzy Q-learning (Li et al., 2012), and genetic-based fuzzy Q-learning (Kuznetsova et al., 2013; Xin et al., 2012). More interestingly, it was discovered that the combination technique outperformed either MPC or Qlearning alone (Liu and Henze, 2006). Barrett et al. (Barrett and Linder, 2015) used Q-learning for the issue of HVAC control in conjunction with Bayesian Learning for predicting occupancy in 2015. Based on the results, a 10% enhancement was observed in energy savings over a programmed control system. Besides, in 2017, deep NN and Deep RL were employed by Wei et al. (Wei et al., 2017), aiming to solve the HVAC control problem, and reported energy savings increases of 20-70% above standard Q-learning. Meanwhile, Chen et al. (Chen et al., 2018) used Q-learning to regulate the window systems and HVAC. As reported, the two buildings studied saved 13% and 23% on energy and reduced discomfort levels by 62% and 80%. Fitted Q Iteration was applied in an investigation by Reymond et al. (Reymond et al., 2018) in 2018 for learning to schedule a variety of domestic equipment, such as dishwashers, water heaters, and heat pumps. Their findings showed that autonomous learning outperformed the centralized learning method by 9.65%. As for managing residential batteries, Wei et al. (Wei et al., 2015) developed a dual iterative Q-learning technique, and in comparison with the baseline, a 32.16% reduction was observed in energy expenses. In addition, Guan et al. (Chenxiao Guan et al., 2015) employed temporal difference learning to aim to manage the battery energy storage with PV panels in the research in 2015. It is noted that temporal difference learning was found to reduce 59.8% of energy expenses. More remarkably, Rayati et al. (Rayati et al., 2015) applied Q-learning to residential energy management in the context of PV installation and energy storage. When determining the best control regime, this research took into account household comfort and CO2 emissions. According to the authors, maximal energy savings reached 40%, along with a 17% decrease in peak load, and a 50% reduction in CO2 societal expenses. Remani et al. (Remani et al., 2019) used Q-learning to schedule numerous household equipment like lights, dish washers, laundry dryers, and so on. Aside from that, the authors also constructed a demand response system based on price, in which a PV panel was incorporated, indicating a 15% reduction in daily energy expenditure. Wen et al. (Wen et al., 2015) suggested an energy management system for demand response for small buildings, allowing for automatic device scheduling to deal with variations in electricity prices. Furthermore, Mocanu et al. (Mocanu et al., 2019) utilized DQL and DPG to improve the system of energy management for 10, 20, and 48 households in the 2018 research. In addition, this investigation looked into the employment of vehicles running on electricity, PV panels, and appliances in the building. As reported, DPG saved 27.4% on power and DQL saved 14.1%. Moreover, the researchers employed Q-learning to exploit the projected 65% potential energy savings for small houses through effective device scheduling, and they demonstrated enhancements according to the baseline. Also, inverse reinforcement learning was applied by Bazenkov et al. (Bazenkov and Goubko, 2018) to forecast consumer appliance consumption, and it was observed that IRL outperformed other machine learning approaches like random forest. In a study by

Jiang *et al.*, a hierarchical multi-agent Q-learning technique was implemented in a microgrid for responding to the dynamic demand as well as manage distributed energy sources (Jiang and Fei, 2015). According to this study, the entire community's energy expenses were reduced by 19%.

4. Existing limitations and perspectives

Al models offer numerous benefits, but they also have certain drawbacks. First, AI models and clever algorithms, like other models driven by data, perform poorly beyond their training range. Therefore, models are restricted to the value range encountered during training. As a result, these retraining strategies can support making sure that AI models efficiently adapt to novel data and circumstances (Barkah et al., 2023). Furthermore, AI models are black-box-based models themselves, so the internals are unknown. They may give a competent forecasting tool, but they lack comprehension of the fundamental characteristics of energy use as well as its behavior. More importantly, the employment of hybrid grey-box models is considered one way to address this. In the aforementioned models, AI models are often integrated with equations based on physics to maximize the benefits of both models while minimizing their drawbacks. Overfitting is another constraint that might impair the effectiveness of AI models as well as smart algorithms. Indeed, overfitting happens when a model learns too much noise from the training data. To overcome this challenge, there are several strategies both within and outside of training to boost generality. Moreover, models may be trained using a suitably large data collection concerning the quantity of inputs (MathWorks, n.d.). Although additional ways exist to assist in ensuring generality, the methods discussed above offer a concise summary of some possible approaches to tackle the specific problem. Furthermore, insufficient hyperparameter selection can result in models with poor performance in predicting and/or needing more time to generate estimation, which is another restriction of AI models. Regardless, in case the hyperparameters of AI models are properly adjusted, intelligent algorithms along with AI models can show great performance and short processing times. Hence, professionals are now required while building AI models (Runge and Zmeureanu, 2019). Furthermore, delays are thought to have a significant impact on system operation. Because latency propagates via a system, an EMS's response is restricted by the slowest connection in the system. Interestingly, while multistage and hybrid AI models are effective and innovative, their real-time performance is questionable and needs research. It is suggested that researchers consider doing mock experiments with energy systems on a small scale to assess the effectiveness of the AI model when systems, controller software, and sensors from other energy resources are taken into account. Indeed, the simple and effective combination of AI could be a significant innovation of the concept. Experiment results that have been validated can guide the future of AI employment in the energy field. Although AI models have been evaluated in a confined setting, more research and effort are required when AI is gradually integrated into a wider system. This results in the core problem with Energy Management Systems, namely real-time operation (Li et al., 2023). However, there exist restraints to utilizing intelligent algorithms in energy management systems because the vast number of publications describe the employment of intelligent methods in simulated versions of energy management issues. It is noticeable that because intelligent algorithms are known as online learning algorithms,

Table 4Summary of identified constraints, solutions, and observations from the Intelligent Energy Prediction Survey

Key Points	Inferences				
AI Model Limitations	 AI models and algorithms have limitations beyond their training range These models are constrained by the value range encountered during training Retraining strategies are used to ensure adaptability to novel data and circumstances Hybrid grey-box models integrate AI models with physics-based equations to enhance understanding and performance. 				
Black-Box Nature of AI Models	 AI models are black-box-based and lack comprehension of fundamental energy use characteristics Hybrid models combine AI and physics-based equations to maximize benefits while minimizing drawbacks This approach enhances forecasting competence and improves understanding of energy behavior 				
Overfitting Challenge	 Overfitting occurs when a model learns noise from training data Strategies within and outside training are used to address overfitting and boost generality Adequate data collection and proper hyperparameter selection are crucial to ensuring model effectiveness 				
Hyperparameter Selection	 Poor hyperparameter selection can result in models with poor performance and longer processing times Properly adjusted hyperparameters enable AI models and algorithms to achieve high performance and short processing times More technicalities are required to build effective AI models. 				
Real-Time Performance	 Delays impact system operation, with an EMS's response limited by the slowest connection Multi-stage and hybrid AI models are innovative but raise questions about real-time performance Mock experiments with energy systems are suggested to assess AI model effectiveness in real-world scenarios. 				
AI Integration into Energy Systems	 AI models have been evaluated in confined settings, but more research is needed for gradual integration into wider systems Challenges exist in utilizing intelligent algorithms due to the predominance of simulated versions in publications Intelligent algorithms need to learn effective control policies through trial and error. 				
Deep Intelligent Algorithm Approaches	 Increasing sensor data volume calls for deep intelligent algorithms to develop successful policies in complex state-action spaces Exploring variants of classic intelligent algorithms is a potential pathway for future research in energy management. 				
Multi-Objective Intelligent Algorithm Issues	 Some energy management challenges are multi-objective intelligent algorithm issues Future studies could investigate the use of meta-learning to address intelligent algorithm challenges in energy management. 				
Future Research	 Future research could address the duration intelligent algorithm agents need to relearn new policies Comparative studies of different algorithms and control methods could be valuable Merging multiple intelligent systems for energy control is a potential research direction. 				

they might be used in a physical-based energy management system with no need to learn in a simulated setting. Hence, intelligent algorithms must learn effective control policies, which reduce energy expenses through error and trial. Apart from that, for this purpose, accurate simulators are required for the intelligent algorithms agent to learn which rules are optimal through simulation. When the aforementioned pre-trained agents are deployed in physical systems, they can further improve their policies (Mason and Grijalva, 2019).

Significantly, due to the increasing volume of data acquired by sensors in the future, it is essential to apply deep intelligent algorithm approaches aiming to build successful policies while dealing with settings with extremely huge state-action spaces. Besides, using various variants of classic intelligent algorithms can be a new pathway for future study in intelligent algorithms for the management of energy. Meanwhile, several energy

management challenges can be multi-objective intelligent algorithm issues. Future studies may also investigate the use of meta-learning to overcome the challenges of intelligent algorithms in energy management. Furthermore, several future research questions have been raised, like how long the intelligent algorithm agent must spend relearning new policies in those situations. More interestingly, another possible future study topic can be experimentally comparing various algorithms as well as other control algorithms. Indeed, further studies might look towards merging several intelligent systems to control energy (Mason and Grijalva, 2019). Table 4 presents the tabulated results of identified constraints and potential solutions, along with key observations stemming from an extensive survey and Fig. 7 illustrates the present focus of research and the potential paths for future research in the field of AI for Energy Data Analytics.

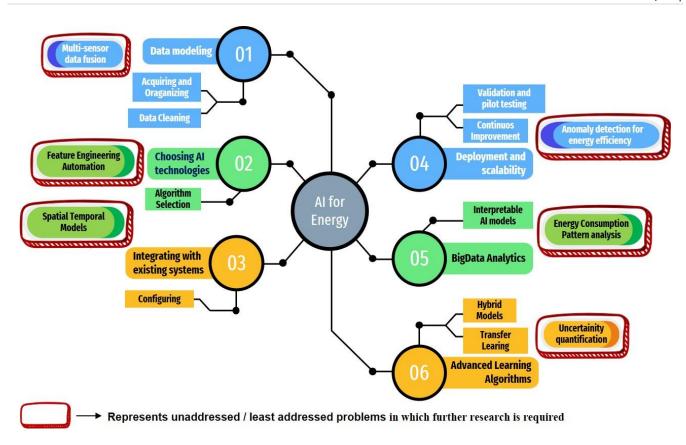


Fig. 7. Current research area and future research directions of AI for energy data analytics

5. Conclusions and future directions in field

In conclusion, the increasing demand for sustainability and concerns about energy exhaustion have made energy management a significant topic in this era of globalization and technological advancement. This paper has explored the applications of artificial intelligence (AI) in energy management, specifically focusing on areas such as demand response, smart grids, and energy forecasting. The use of intelligent algorithms and artificial neural networks (ANNs) in energy management systems has been discussed. The review emphasizes the importance of AI models in predicting energy consumption, load patterns, and resource planning to ensure consistent efficient resource performance and utilization. implementation of AI in energy management has shown promising results, with reported energy savings of over 25%. However, it is important to acknowledge that training AI model requires large volumes of data, necessitating the utilization of big data systems and data mining techniques to identify new functions and associations that can enhance AI performance. Additionally, the integration of advanced digital technologies such as the Internet of Things and blockchain can further enhance intelligent energy management. As a future scope of this work, it is posited that the integration of multiple AI techniques to generate hybrid models has the potential to significantly improve prediction accuracy. The future investigations should focus on deep learning models, long-term prediction, component-based target variables, ensemble models, lighting models, grey-box models, automated architecture selection methods, and sliding window re-training.

These directions have the potential to improve energy management models, enhance energy usage, contribute to data science, and facilitate big data analysis.

References

Abdalla, O., Rezk, H., Ahmed, E.M., (2019). Wind driven optimization algorithm based global MPPT for PV system under non-uniform solar irradiance. *Sol. Energy 180*, 429–444. https://doi.org/10.1016/j.solener.2019.01.056

Abdallah, M., Abu Talib, M., Feroz, S., Nasir, Q., Abdalla, H., Mahfood, B., (2020). Artificial intelligence applications in solid waste management: A systematic research review. *Waste Manag.* 109, 231–246. https://doi.org/10.1016/j.wasman.2020.04.057

Abedinia, O., Amjady, N., Ghadimi, N., (2018). Solar energy forecasting based on hybrid neural network and improved metaheuristic algorithm. *Comput. Intell.* 34, 241–260. https://doi.org/10.1111/coin.12145

Adhikari, D.R., Techato, K., Jariyaboon, R., (2024). A systematic literature review on renewable energy technologies for energy sustainability in Nepal: Key challenges and opportunities. Int. J. Renew. *Energy Dev. 13*, 206–222. https://doi.org/10.61435/ijred.2024.60032

Ağbulut, Ü., (2022a). A novel stochastic model for very short-term wind speed forecasting in the determination of wind energy potential of a region: A case study from Turkey. Sustain. Energy Technol. Assessments 51, 101853. https://doi.org/10.1016/j.seta.2021.101853

Ağbulut, Ü., (2022b). Forecasting of transportation-related energy demand and CO2 emissions in Turkey with different machine learning algorithms. *Sustain. Prod. Consum.* 29, 141–157. https://doi.org/10.1016/j.spc.2021.10.001

Ağbulut, Ü., Gürel, A.E., Biçen, Y., (2021). Prediction of daily global solar

- radiation using different machine learning algorithms: Evaluation and comparison. *Renew. Sustain. Energy Rev. 135*, 110114. https://doi.org/10.1016/j.rser.2020.110114
- Ağbulut, Ü., Gürel, A.E., Ergün, A., Ceylan, İ., (2020). Performance assessment of a V-trough photovoltaic system and prediction of power output with different machine learning algorithms. *J. Clean. Prod. 268*, 122269. https://doi.org/10.1016/j.jclepro.2020.122269
- Aguilar, J., Garces-Jimenez, A., R-Moreno, M.D., García, R., (2021). A systematic literature review on the use of artificial intelligence in energy self-management in smart buildings. *Renew. Sustain. Energy Rev. 151*, 111530. https://doi.org/10.1016/j.rser.2021.111530
- Ahmad, T., Zhang, D., Huang, C., Zhang, H., Dai, N., Song, Y., Chen, H., (2021). Artificial intelligence in sustainable energy industry: Status Quo, challenges and opportunities. *J. Clean. Prod. 289*. https://doi.org/10.1016/j.jclepro.2021.125834
- Ahmed, W., Ansari, H., Khan, B., Ullah, Z., Ali, S.M., Mehmood, C.A.A., Qureshi, M.B., Hussain, I., Jawad, M., Khan, M.U.S., Ullah, A., Nawaz, R., (2020a). Machine learning based energy management model for smart grid and renewable energy districts. *IEEE Access 8*, 185059–185078. https://doi.org/10.1109/ACCESS.2020.3029943
- Ahmed, W., Ansari, H., Khan, B., Ullah, Z., Ali, S.M., Mehmood, C.A.A., Qureshi, M.B., Hussain, I., Jawad, M., Khan, M.U.S., Ullah, A., Nawaz, R., (2020b). Machine Learning Based Energy Management Model for Smart Grid and Renewable Energy Districts. *IEEE Access 8*, 185059–185078. https://doi.org/10.1109/ACCESS.2020.3029943
- Akhter, M.N., Mekhilef, S., Mokhlis, H., Shah, N.M., (2019). Review on forecasting of photovoltaic power generation based on machine learning and metaheuristic techniques. *IET Renew. Power Gener.* 13, 1009–1023. https://doi.org/10.1049/iet-rpg.2018.5649
- Al Sasongko, S.M., Jayanti, E.D., Ariessaputra, S., (2022). Application of Gray Scale Matrix Technique for Identification of Lombok Songket Patterns Based on Backpropagation Learning. *JOIV Int. J. Informatics Vis. 6*, 835–841. https://doi.org/10.30630/joiv.6.4.1532
- Al Sumarmad, K.A., Sulaiman, N., Wahab, N.I.A., Hizam, H., (2022). Energy Management and Voltage Control in Microgrids Using Artificial Neural Networks, PID, and Fuzzy Logic Controllers. Energies 15, 303. https://doi.org/10.3390/en15010303
- Albarakati, A.J., Boujoudar, Y., Azeroual, M., Jabeur, R., Aljarbouh, A., El Moussaoui, H., Lamhamdi, T., Ouaaline, N., (2021). Real-Time Energy Management for DC Microgrids Using Artificial Intelligence. *Energies* 14, 5307. https://doi.org/10.3390/en14175307
- Ali, A., Muhadi, Al Rasyid, M.U.H., Syarif, I., (2023). Development User Interface Hospital Management Information System Based on a Heuristic Evaluation Approach in Surabaya Hospital Medical Services. *Int. J. Adv. Sci. Eng. Inf. Technol.* 13, 1456–1462. https://doi.org/10.18517/jjaseit.13.4.16529
- Alsafasfeh, Q., (2020). An Efficient Algorithm for Power Prediction in PV Generation System. *Int. J. Renew. Energy Dev. 9*, 207–216. https://doi.org/10.14710/ijred.9.2.207-216
- Anandika, A., Ferdian, R., Eriyandha, A., Suwandi, R., Hafidz, M., (2023). Smart Room System for Paralysis Patients with Mindwave EEG Sensor Control. JOIV Int. J. Informatics Vis. 7, 2558–2568. https://doi.org/10.30630/joiv.7.4.01745
- Aniza, R., Chen, W.-H., Pétrissans, A., Hoang, A.T., Ashokkumar, V., Pétrissans, M., (2023). A review of biowaste remediation and valorization for environmental sustainability. Artificial intelligence approach. *Environ. Pollut.* 324, 121363. https://doi.org/10.1016/j.envpol.2023.121363
- Antonopoulos, I., Robu, V., Couraud, B., Kirli, D., Norbu, S., Kiprakis, A., Flynn, D., Elizondo-Gonzalez, S., Wattam, S., (2020). Artificial intelligence and machine learning approaches to energy demand-side response: A systematic review. *Renew. Sustain. Energy Rev. 130*, 109899. https://doi.org/10.1016/j.rser.2020.109899
- Arabali, A., Ghofrani, M., Etezadi-Amoli, M., Fadali, M.S., Baghzouz, Y., (2013). Genetic-Algorithm-Based Optimization Approach for Energy Management. *IEEE Trans. Power Deliv. 28*, 162–170. https://doi.org/10.1109/TPWRD.2012.2219598

- Arcos-Aviles, D., Pascual, J., Marroyo, L., Sanchis, P., Guinjoan, F., (2018). Fuzzy logic-based energy management system design for residential grid-connected microgrids. *IEEE Trans. Smart Grid 9*, 530–543. https://doi.org/10.1109/TSG.2016.2555245
- Armin Razmjoo, A., Sumper, A., Davarpanah, A., (2019). Development of sustainable energy indexes by the utilization of new indicators: A comparative study. *Energy Reports 5*, 375–383. https://doi.org/10.1016/j.egyr.2019.03.006
- Atmaca, A., Atmaca, N., (2015). Life cycle energy (LCEA) and carbon dioxide emissions (LCCO2A) assessment of two residential buildings in Gaziantep, Turkey. *Energy Build.* 102, 417–431. https://doi.org/10.1016/j.enbuild.2015.06.008
- Aung, H.N., Khambadkone, A.M., Srinivasan, D., Logenthiran, T., (2010). Agent-based intelligent control for real-time operation of a microgrid, in: 2010 Joint International Conference on Power Electronics, Drives and Energy Systems & 2010 Power India. *IEEE*, pp. 1–6. https://doi.org/10.1109/PEDES.2010.5712495
- Aviles, D.A., Guinjoan, F., Barricarte, J., Marroyo, L., Sanchis, P., Valderrama, H., (2012). Battery management fuzzy control for a grid- tied microgrid with renewable generation, in: IECON 2012 38th Annual Conference on IEEE Industrial Electronics Society.

 IEEE, pp. 5607–5612. https://doi.org/10.1109/IECON.2012.6389008
- Bacanin, N., Bezdan, T., Tuba, E., Strumberger, I., Tuba, M., (2020).

 Monarch Butterfly Optimization Based Convolutional Neural
 Network Design. *Mathematics 8,* 936.

 https://doi.org/10.3390/math8060936
- Bakay, M.S., Ağbulut, Ü., (2021). Electricity production based forecasting of greenhouse gas emissions in Turkey with deep learning, support vector machine and artificial neural network algorithms. J. Clean. Prod. 285, 125324. https://doi.org/10.1016/j.jclepro.2020.125324
- Bakır, H., Ağbulut, Ü., Gürel, A.E., Yıldız, G., Güvenç, U., Soudagar, M.E.M., Hoang, A.T., Deepanraj, B., Saini, G., Afzal, A., (2022). Forecasting of future greenhouse gas emission trajectory for India using energy and economic indexes with various metaheuristic algorithms. *J. Clean. Prod.* 360, 131946. https://doi.org/10.1016/j.jclepro.2022.131946
- Barkah, A.S., Selamat, S.R., Abidin, Z.Z., Wahyudi, R., (2023). Impact of Data Balancing and Feature Selection on Machine Learning-based Network Intrusion Detection. *JOIV Int. J. Informatics Vis.* 7, 241–248. https://doi.org/10.30630/joiv.7.1.1041
- Barrett, E., Linder, S., (2015). Autonomous HVAC Control, *A Reinforcement Learning Approach*. pp. 3–19. https://doi.org/10.1007/978-3-319-23461-8_1
- Barricarte, J.J., Martín, I., Sanchis, P., Marroyo, L., (2011). Energy management strategies for grid integration of microgrids based on renewable energy sources, in: *Int. Conf. Sustain. Energy Technol. pp. 4–7.*
- Bazenkov, N., Goubko, M., (2018). Advanced Planning of Home Appliances with Consumer's Preference Learning. pp. 249–259. https://doi.org/10.1007/978-3-030-00617-4_23
- Bechouat, M., Younsi, A., Sedraoui, M., Soufi, Y., Yousfi, L., Tabet, I., Touafek, K., (2017). Parameters identification of a photovoltaic module in a thermal system using meta-heuristic optimization methods. *Int. J. Energy Environ. Eng. 8*, 331–341. https://doi.org/10.1007/s40095-017-0252-6
- Bessa, R.J., Trindade, A., Silva, C.S.P., Miranda, V., (2015). Probabilistic solar power forecasting in smart grids using distributed information. *Int. J. Electr. Power Energy Syst.* 72, 16–23. https://doi.org/10.1016/j.ijepes.2015.02.006
- Bisri, A., Man, M., (2023). Machine Learning Algorithms Based on Sampling Techniques for Raisin Grains Classification. JOIV Int. J. Informatics Vis. 7, 7–14. https://doi.org/10.30630/joiv.7.1.970
- Biswas, P.P., Chen, W.-H., Lam, S.S., Park, Y.-K., Chang, J.-S., Hoang, A.T., (2023). A comprehensive study of artificial neural network for sensitivity analysis and hazardous elements sorption predictions via bone char for wastewater treatment. *J. Hazard. Mater.* 133154. https://doi.org/10.1016/j.jhazmat.2023.133154
- Bogaraj, T., Kanakaraj, J., (2016). Intelligent energy management control for independent microgrid. *Sādhanā 41*, 755–769. https://doi.org/10.1007/s12046-016-0515-6
- Boudoudouh, S., Maâroufi, M., (2018). Multi agent system solution to microgrid implementation. Sustain. Cities Soc. 39, 252–261.

https://doi.org/10.1016/j.scs.2018.02.020

- Bruni, G., Cordiner, S., Mulone, V., Rocco, V., Spagnolo, F., (2015). A study on the energy management in domestic micro-grids based on Model Predictive Control strategies. *Energy Convers. Manag.* 102, 50–58. https://doi.org/10.1016/j.enconman.2015.01.067
- Bukar, A.L., Tan, C.W., Said, D.M., Dobi, A.M., Ayop, R., Alsharif, A., (2022). Energy management strategy and capacity planning of an autonomous microgrid: Performance comparison of metaheuristic optimization searching techniques. *Renew. Energy Focus* 40, 48–66. https://doi.org/10.1016/j.ref.2021.11.004
- Cao, B., Dong, W., Lv, Z., Gu, Y., Singh, S., Kumar, P., (2020a). Hybrid Microgrid Many-Objective Sizing Optimization With Fuzzy Decision. *IEEE Trans. Fuzzy Syst. 28*, 2702–2710. https://doi.org/10.1109/TFUZZ.2020.3026140
- Cao, B., Wang, X., Zhang, W., Song, H., Lv, Z., (2020b). A Many-Objective Optimization Model of Industrial Internet of Things Based on Private Blockchain. *IEEE Netw. 34*, 78–83. https://doi.org/10.1109/MNET.011.1900536
- Cao, B., Zhao, J., Gu, Y., Fan, S., Yang, P., (2020c). Security-Aware Industrial Wireless Sensor Network Deployment Optimization. *IEEE Trans. Ind. Informatics* 16, 5309–5316. https://doi.org/10.1109/TII.2019.2961340
- Cao, B., Zhao, J., Gu, Y., Ling, Y., Ma, X., (2020d). Applying graph-based differential grouping for multiobjective large-scale optimization. Swarm Evol. Comput. 53, 100626. https://doi.org/10.1016/j.swevo.2019.100626
- Cao, B., Zhao, J., Yang, P., Gu, Y., Muhammad, K., Rodrigues, J.J.P.C., de Albuquerque, V.H.C., (2020e). Multiobjective 3-D Topology Optimization of Next-Generation Wireless Data Center Network. IEEE Trans. Ind. Informatics 16, 3597–3605. https://doi.org/10.1109/TII.2019.2952565
- Cavalcante, L., Bessa, R.J., Reis, M., Browell, J., (2017). LASSO vector autoregression structures for very short-term wind power forecasting. *Wind Energy 20,* 657–675. https://doi.org/10.1002/we.2029
- Chandrasekaran, Y.J., Gunamony, S.L., Chandran, B.P., (2019). Integration of 5G Technologies in Smart Grid Communication-A Short Survey. *Int. J. Renew. Energy Dev. 8*, 275–283. https://doi.org/10.14710/ijred.8.3.275-283
- Chaoraingern, J., Tipsuwanporn, V., Numsomran, A., (2023). Artificial Intelligence for the Classification of Plastic Waste Utilizing TinyML on Low-Cost Embedded Systems. *Int. J. Adv. Sci. Eng. Inf. Technol.* 13, 2328–2337. https://doi.org/10.18517/ijaseit.13.6.18958
- Chau, M.Q., Nguyen, X.P., Huynh, T.T., Chu, V.D., Le, T.H., Nguyen, T.P., Nguyen, D.T., (2021). Prospects of application of IoT-based advanced technologies in remanufacturing process towards sustainable development and energy-efficient use. *Energy Sources, Part A Recover. Util. Environ. Eff.* 1–25. https://doi.org/10.1080/15567036.2021.1994057
- Chen, H., Qiao, H., Xu, L., Feng, Q., Cai, K., (2019). A fuzzy optimization strategy for the implementation of RBF LSSVR model in vis–NIR analysis of pomelo maturity. *IEEE Trans. Ind. Informatics* 15, 5971–5979.
- Chen, Hao, Heidari, A.A., Chen, Huiling, Wang, M., Pan, Z., Gandomi, A.H., (2020). Multi-population differential evolution-assisted Harris hawks optimization: Framework and case studies. Futur. Gener. Comput. Syst. 111, 175–198. https://doi.org/10.1016/j.future.2020.04.008
- Chen, W.-H., Aniza, R., Arpia, A.A., Lo, H.-J., Hoang, A.T., Goodarzi, V., Gao, J., (2022a). A comparative analysis of biomass torrefaction severity index prediction from machine learning. *Appl. Energy* 324, 119689. https://doi.org/10.1016/j.apenergy.2022.119689
- Chen, W.-H., Wang, J.-S., Chang, M.-H., Mutuku, J.K., Hoang, A.T., (2021). Efficiency improvement of a vertical-axis wind turbine using a deflector optimized by Taguchi approach with modified additive method. *Energy Convers. Manag.* 245, 114609. https://doi.org/10.1016/j.enconman.2021.114609
- Chen, W.-H., Wang, J.-S., Chang, M.-H., Tuan Hoang, A., Shiung Lam, S., Kwon, E.E., Ashokkumar, V., (2022b). Optimization of a vertical axis wind turbine with a deflector under unsteady wind conditions via Taguchi and neural network applications. *Energy Convers. Manag. 254*, 115209. https://doi.org/10.1016/j.enconman.2022.115209

- Chen, Y., Norford, L.K., Samuelson, H.W., Malkawi, A., (2018). Optimal control of HVAC and window systems for natural ventilation through reinforcement learning. *Energy Build.* 169, 195–205. https://doi.org/10.1016/j.enbuild.2018.03.051
- Chen, Z., Liu, Y., Zhang, Y., Lei, Z., Chen, Zheng, Li, G., (2022). A neural network-based ECMS for optimized energy management of plug-in hybrid electric vehicles. *Energy 243*, 122727. https://doi.org/10.1016/j.energy.2021.122727
- Chenxiao Guan, Wang, Y., Xue Lin, Nazarian, S., Pedram, M., (2015).

 Reinforcement learning-based control of residential energy storage systems for electric bill minimization, in: 2015–12th Annual IEEE Consumer Communications and Networking Conference (CCNC). *IEEE*, pp. 637–642. https://doi.org/10.1109/CCNC.2015.7158054
- Chiñas-Palacios, C., Vargas-Salgado, C., Aguila-Leon, J., Hurtado-Pérez, E., (2021a). A cascade hybrid PSO feed-forward neural network model of a biomass gasification plant for covering the energy demand in an AC microgrid. *Energy Convers. Manag. 232*, 113896. https://doi.org/10.1016/j.enconman.2021.113896
- Chiñas-Palacios, C., Vargas-Salgado, C., Aguila-Leon, J., Hurtado-Pérez, E., (2021b). A cascade hybrid PSO feed-forward neural network model of a biomass gasification plant for covering the energy demand in an AC microgrid. *Energy Convers. Manag. 232*, 113896. https://doi.org/10.1016/j.enconman.2021.113896
- Chou, J.-S., Hsu, S.-C., Ngo, N.-T., Lin, C.-W., Tsui, C.-C., (2019a).

 Hybrid Machine Learning System to Forecast Electricity
 Consumption of Smart Grid-Based Air Conditioners. *IEEE Syst.*J. 13, 3120–3128.

 https://doi.org/10.1109/JSYST.2018.2890524
- Chou, J.-S., Hsu, S.-C., Ngo, N.-T., Lin, C.-W., Tsui, C.-C., (2019b). Hybrid Machine Learning System to Forecast Electricity Consumption of Smart Grid-Based Air Conditioners. *IEEE Syst. J.* 3120–3128. https://doi.org/10.1109/JSYST.2018.2890524
- Corizzo, R., Ceci, M., Fanaee-T, H., Gama, J., (2021). Multi-aspect renewable energy forecasting. *Inf. Sci. (Ny).* 546, 701–722. https://doi.org/10.1016/j.ins.2020.08.003
- Dai, P., Yu, W., Wen, G., Baldi, S., (2020). Distributed Reinforcement Learning Algorithm for Dynamic Economic Dispatch With Unknown Generation Cost Functions. IEEE Trans. Ind. Informatics 16, 2258–2267. https://doi.org/10.1109/TII.2019.2933443
- de Ville, B., (2013). Decision trees. Wiley Interdiscip. Rev. Comput. Stat. 5, 448–455. https://doi.org/10.1002/wics.1278
- Desale, S., Rasool, A., Andhale, S., Rane, P., (2015). Heuristic and metaheuristic algorithms and their relevance to the real world: a survey. Int. J. Comput. Eng. Res. Trends 351, 2349–7084.
- Dobbelaere, M.R., Plehiers, P.P., Van de Vijver, R., Stevens, C. V., Van Geem, K.M., (2021). Machine Learning in Chemical Engineering: Strengths, Weaknesses, Opportunities, and Threats. *Engineering* 7, 1201–1211. https://doi.org/10.1016/j.eng.2021.03.019
- Domachowski, Z., (2021). Minimizing Greenhouse Gas Emissions From Ships Using a Pareto Multi-Objective Optimization Approach. Polish Marit. Res. 28, 96–101. https://doi.org/10.2478/pomr-2021-0026
- Dong, V.H., Sharma, P., (2023). Optimized conversion of waste vegetable oil to biofuel with Meta heuristic methods and design of experiments. *J. Emerg. Sci. Eng. 1*, 22–28. https://doi.org/10.61435/jese.2023.4
- Dong, W., Yang, Q., Fang, X., Ruan, W., (2021). Adaptive optimal fuzzy logic based energy management in multi-energy microgrid considering operational uncertainties. Appl. Soft Comput. 98, 106882. https://doi.org/10.1016/j.asoc.2020.106882
- Doukas, H., Patlitzianas, K.D., Iatropoulos, K., Psarras, J., (2007). Intelligent building energy management system using rule sets. *Build. Environ.* 42, 3562–3569. https://doi.org/10.1016/j.buildenv.2006.10.024
- Drzewiecki, M., Guziński, J., (2023). Design of an Autonomous IoT Node Powered by a Perovskite-Based Wave Energy Converter. *Polish Marit. Res. 30*, 142–152. https://doi.org/10.2478/pomr-2023-0047
- Duan, Jikai, Zuo, H., Bai, Y., Duan, Jizheng, Chang, M., Chen, B., (2021).
 Short-term wind speed forecasting using recurrent neural networks with error correction. *Energy 217*, 119397.

- https://doi.org/10.1016/j.energy.2020.119397
- Duraković, B., Halilovic, M., (2023). Industry 4.0: The New Quality Management Paradigm in Era of Industrial Internet of Things. JOIV Int. J. Informatics Vis. 7, 580–587. https://doi.org/10.30630/joiv.7.2.1738
- El-Shafay, A.S., Gad, M.S., Ağbulut, Ü., Attia, E.-A., (2023). Optimization of performance and emission outputs of a CI engine powered with waste fat biodiesel: A detailed RSM, fuzzy multi-objective and MCDM application. *Energy 275*, 127356. https://doi.org/10.1016/j.energy.2023.127356
- Elsheikh, A.H., Sharshir, S.W., Abd Elaziz, M., Kabeel, A.E., Guilan, W., Haiou, Z., (2019). Modeling of solar energy systems using artificial neural network: A comprehensive review. *Sol. Energy* 180, 622–639. https://doi.org/10.1016/j.solener.2019.01.037
- Erfianto, B., Rahmatsyah, A., (2022). Application of ARIMA Kalman Filter with Multi-Sensor Data Fusion Fuzzy Logic to Improve Indoor Air Quality Index Estimation. *JOIV Int. J. Informatics Vis. 6*, 771–777. https://doi.org/10.30630/joiv.6.4.889
- Eseye, A.T., Zhang, J., Zheng, D., (2018). Short-term photovoltaic solar power forecasting using a hybrid Wavelet-PSO-SVM model based on SCADA and Meteorological information. *Renew. Energy* 118, 357–367. https://doi.org/10.1016/J.RENENE.2017.11.011
- Faia, R., Pinto, T., Vale, Z., Corchado, J., (2017). An Ad-Hoc Initial Solution Heuristic for Metaheuristic Optimization of Energy Market Participation Portfolios. *Energies 10*, 883. https://doi.org/10.3390/en10070883
- Förderer, K., Ahrens, M., Bao, K., Mauser, I., Schmeck, H., (2018). Towards the Modeling of Flexibility Using Artificial Neural Networks in Energy Management and Smart Grids, in: Proceedings of the Ninth International Conference on Future Energy Systems. ACM, New York, NY, USA, pp. 85–90. https://doi.org/10.1145/3208903.3208915
- Fossati, J.P., Galarza, A., Martín-Villate, A., Echeverría, J.M., Fontán, L., (2015). Optimal scheduling of a microgrid with a fuzzy logic controlled storage system. *Int. J. Electr. Power Energy Syst.* 68, 61– 70. https://doi.org/10.1016/j.ijepes.2014.12.032
- Fu, X., Pace, P., Aloi, G., Yang, L., Fortino, G., (2020). Topology optimization against cascading failures on wireless sensor networks using a memetic algorithm. *Comput. Networks* 177, 107327. https://doi.org/10.1016/j.comnet.2020.107327
- Fuadi, A.Z., Haq, I.N., Leksono, E., (2021). Support Vector Machine to Predict Electricity Consumption in the Energy Management Laboratory.
- Furman, J., Seamans, R., (2019). AI and the Economy. *Innov. Policy Econ.* 19, 161–191. https://doi.org/10.1086/699936
- Galván, I.M., Valls, J.M., Cervantes, A., Aler, R., (2017). Multi-objective evolutionary optimization of prediction intervals for solar energy forecasting with neural networks. *Inf. Sci. (Ny).* 418–419, 363–382. https://doi.org/10.1016/j.ins.2017.08.039
- Gangolells, M., Casals, M., Forcada, N., Macarulla, M., Giretti, A., (2016). Energy performance assessment of an intelligent energy management system. *Renew. Sustain. Energy Rev. 55*, 662–667. https://doi.org/10.1016/j.rser.2015.11.006
- Gao, J.B., Gunn, S.R., Harris, C.J., (2003). SVM regression through variational methods and its sequential implementation. *Neurocomputing* 55, 151–167. https://doi.org/10.1016/S0925-2312(03)00365-5
- Goswami, P., Mukherjee, A., Hazra, R., Yang, L., Ghosh, U., Qi, Y., Wang, H., (2022). AI Based Energy Efficient Routing Protocol for Intelligent Transportation System. IEEE Trans. Intell. Transp. Syst. 23, 1670–1679. https://doi.org/10.1109/TITS.2021.3107527
- Goyal, D., Goyal, T., Mahla, S.K., Goga, G., Dhir, A., Balasubramanian, D., Hoang, A.T., Wae-Hayee, M., Josephin, J.S.F., Sonthalia, A., Varuvel, E.G., Brindhadevi, K., (2023). Application of Taguchi design in optimization of performance and emissions characteristics of n-butanol/diesel/biogas under dual fuel mode. *Fuel 338*, 127246. https://doi.org/10.1016/j.fuel.2022.127246
- Halabi, L.M., Mekhilef, S., Hossain, M., (2018). Performance evaluation of hybrid adaptive neuro-fuzzy inference system models for predicting monthly global solar radiation. *Appl. Energy 213*, 247–261. https://doi.org/10.1016/j.apenergy.2018.01.035
 Haleem, A., Javaid, M., Khan, I.H., (2019). Current status and
- Haleem, A., Javaid, M., Khan, I.H., (2019). Current status and applications of Artificial Intelligence (AI) in medical field: An overview. Curr. Med. Res. Pract. 9, 231–237.

- https://doi.org/10.1016/j.cmrp.2019.11.005
- Han, L., Jiao, X., Zhang, Z., (2020). Recurrent Neural Network-Based Adaptive Energy Management Control Strategy of Plug-In Hybrid Electric Vehicles Considering Battery Aging. *Energies 13*, 202. https://doi.org/10.3390/en13010202
- Han, T., Wang, Z., Meng, H., (2022). End-to-end capacity estimation of Lithium-ion batteries with an enhanced long short-term memory network considering domain adaptation. J. Power Sources 520, 230823. https://doi.org/10.1016/j.jpowsour.2021.230823
- Haque, R., Quek, A., Ting, C., Goh, H., Hasan, R., (2024). Classification Techniques Using Machine Learning for Graduate Student Employability Predictions. *Int. J. Adv. Sci. Eng. Inf. Technol.* 14, 45–56.
- Hasnaoui, A., Omari, A., Azzouz, Z. eddine, Danoune, M.B., Arini, N.R., (2023). Reduction of Electricity Cost of Residential Home Using PSO and WOA Optimization Method. *Int. J. Adv. Sci. Eng. Inf. Technol.* 13, 828–834. https://doi.org/10.18517/ijaseit.13.3.18374
- Hoang, A.T., Nguyen, X.P., Le, A.T., Huynh, T.T., Pham, V.V., (2021).
 COVID-19 and the Global Shift Progress to Clean Energy. J.
 Energy Resour. Technol. 143. https://doi.org/10.1115/1.4050779
- Hoang, A.T., Pandey, A., Lichtfouse, E., Bui, V.G., Veza, I., Nguyen, H.L., Nguyen, X.P., (2023a). Green hydrogen economy: Prospects and policies in Vietnam. *Int. J. Hydrogen Energy 48*, 31049–31062. https://doi.org/10.1016/j.ijhydene.2023.05.306
- Hoang, A.T., Pandey, A., Martinez De Osés, F.J., Chen, W.-H., Said, Z., Ng, K.H., Ağbulut, Ü., Tarełko, W., Ölçer, A.I., Nguyen, X.P., (2023b). Technological solutions for boosting hydrogen role in decarbonization strategies and net-zero goals of world shipping: Challenges and perspectives. *Renew. Sustain. Energy Rev. 188*, 113790. https://doi.org/10.1016/j.rser.2023.113790
- Horný, M., (2014). Bayesian networks. Bost. Univ. Sch. Public Heal. 17.
 Houssein, E.H., (2019). Machine Learning and Meta-heuristic Algorithms for Renewable Energy: A Systematic Review. pp. 165–187. https://doi.org/10.1007/978-981-13-5995-8_7
- Hu, B., (2018). Application of Evaluation Algorithm for Port Logistics Park Based on Pca-Svm Model. *Polish Marit. Res.* 25, 29–35. https://doi.org/10.2478/pomr-2018-0109
- Hu, J., Chen, H., Heidari, A.A., Wang, M., Zhang, X., Chen, Y., Pan, Z., (2021). Orthogonal learning covariance matrix for defects of grey wolf optimizer: Insights, balance, diversity, and feature selection. Knowledge-Based Syst. 213, 106684. https://doi.org/10.1016/j.knosys.2020.106684
- Hu, Z., Qin, W., (2017). Fuzzy Method and Neural Network Model Parallel Implementation of Multi-Layer Neural Network Based on Cloud Computing for Real Time Data Transmission in Large Offshore Platform. *Polish Marit. Res.* 24, 39–44. https://doi.org/10.1515/pomr-2017-0062
- Ihsan, A.F., Darmadi, Uttunggadewa, S., Rahmawati, S.D., Giovanni, I., Himawan, S.N., (2023). Performance Analysis of Deep Learning Implementation in Operational Condition Forecasting of a Gas Transmission Pipeline Network. *Int. J. Adv. Sci. Eng. Inf. Technol.* 13, 1423–1429. https://doi.org/10.18517/ijaseit.13.4.18250
- Ikeda, S., Nagai, T., (2021). A novel optimization method combining metaheuristics and machine learning for daily optimal operations in building energy and storage systems. *Appl. Energy 289*, 116716. https://doi.org/10.1016/j.apenergy.2021.116716
- Ilham, N.I., Hussin, M.Z., Dahlan, N.Y., Setiawan, E.A., (2022). Prospects and Challenges of Malaysia's Distributed Energy Resources in Business Models Towards Zero Carbon Emission and Energy Security. *Int. J. Renew. Energy Dev.* 11, 1089–1100. https://doi.org/10.14710/ijred.2022.45662
- Issa, E., Al-Gazzar, M., Seif, M., (2022). Energy management of Renewable Energy Sources based on Support Vector Machine. Int. J. Renew. Energy Res. 12. https://doi.org/10.20508/ijrer.v12i2.12897.g8461
- Jadhav, A.M., Patne, N.R., (2017). Priority-Based Energy Scheduling in a Smart Distributed Network With Multiple Microgrids. *IEEE Trans. Ind. Informatics* 13, 3134–3143. https://doi.org/10.1109/TII.2017.2671923
- Jain, D.K., Neelakandan, S., Veeramani, T., Bhatia, S., Memon, F.H., (2022). Design of fuzzy logic based energy management and traffic predictive model for cyber physical systems. *Comput. Electr. Eng.* 102, 108135.

https://doi.org/10.1016/j.compeleceng.2022.108135

- Jawad, M., Qureshi, M.B., Khan, M.U.S., Ali, S.M., Mehmood, A., Khan, B., Wang, X., Khan, S.U., (2021). A Robust Optimization Technique for Energy Cost Minimization of Cloud Data Centers. IEEE Trans. Cloud Comput. 9, 447–460. https://doi.org/10.1109/TCC.2018.2879948
- Jha, S.K., Bilalovic, J., Jha, A., Patel, N., Zhang, H., (2017). Renewable energy: Present research and future scope of Artificial Intelligence. *Renew. Sustain. Energy Rev.* 77, 297–317. https://doi.org/10.1016/j.rser.2017.04.018
- Jiang, B., Fei, Y., (2015). Smart Home in Smart Microgrid: A Cost-Effective Energy Ecosystem With Intelligent Hierarchical Agents. IEEE Trans. Smart Grid 6, 3–13. https://doi.org/10.1109/TSG.2014.2347043
- Jiang, P., Li, R., Lu, H., Zhang, X., (2020). Modeling of electricity demand forecast for power system. *Neural Comput. Appl. 32*, 6857–6875. https://doi.org/10.1007/s00521-019-04153-5
- Jo, T., (2021). Machine Learning Foundations. Springer International Publishing, Cham. https://doi.org/10.1007/978-3-030-65900-4
- Karaağaç, M.O., Ergün, A., Ağbulut, Ü., Gürel, A.E., Ceylan, İ., (2021).
 Experimental analysis of CPV/T solar dryer with nano-enhanced PCM and prediction of drying parameters using ANN and SVM algorithms. Sol. Energy 218, 57–67.
 https://doi.org/10.1016/j.solener.2021.02.028
- Kaytez, F., Taplamacioglu, M.C., Cam, E., Hardalac, F., (2015). Forecasting electricity consumption: A comparison of regression analysis, neural networks and least squares support vector machines. *Int. J. Electr. Power Energy Syst.* 67, 431–438. https://doi.org/10.1016/j.ijepes.2014.12.036
- Khan, P.W., Byun, Y.-C., Lee, S.-J., Kang, D.-H., Kang, J.-Y., Park, H.-S., (2020). Machine Learning-Based Approach to Predict Energy Consumption of Renewable and Nonrenewable Power Sources. *Energies* 13, 4870. https://doi.org/10.3390/en13184870
- Kian, A.Y., Lim, S.C., (2023). On the Potential of Solar Energy for Chemical and Metal Manufacturing Plants in Malaysia. Int. J. Adv. Sci. Eng. Inf. Technol. 13, 1898–1904. https://doi.org/10.18517/ijaseit.13.5.19052
- Kim, J., Moon, J., Hwang, E., Kang, P., (2019). Recurrent inception convolution neural network for multi short-term load forecasting. *Energy Build.* 194, 328–341. https://doi.org/10.1016/j.enbuild.2019.04.034
- Kim, M., Choi, W., Jeon, Y., Liu, L., (2019). A Hybrid Neural Network Model for Power Demand Forecasting. *Energies* 12, 931. https://doi.org/10.3390/en12050931
- Kim, S., (2024). Development of a TPACK Educational Program to Enhance Pre-service Teachers' Teaching Expertise in Artificial Intelligence Convergence Education. *Int. J. Adv. Sci. Eng. Inf. Technol.* 14, 1–9.
- Kim, S.W., Go, H.N., Hong, S.J., Lee, Y., (2023). An Approach to the Utilization of Design Thinking in Artificial Intelligence Education. Int. J. Adv. Sci. Eng. Inf. Technol. 13, 2198–2204. https://doi.org/10.18517/jjaseit.13.6.19042
- Kommuri, N.K., McGordon, A., Allen, A., Quang Truong, D., (2020). Evaluation of a Modified Equivalent Fuel-Consumption Minimization Strategy Considering Engine Start Frequency and Battery Parameters for a Plugin Hybrid Two-Wheeler. *Energies* 13, 3122. https://doi.org/10.3390/en13123122
- Kucęba, R., Zawada, M., Szajt, M., Kowalik, J., (2018). Prosumer energy as a stimulator of micro- Smart Grids development - on the consumer side. *IOP Conf. Ser. Earth Environ. Sci.* 164, 012003. https://doi.org/10.1088/1755-1315/164/1/012003
- Kumar, K., Thakur, G.S.M., (2012). Advanced Applications of Neural Networks and Artificial Intelligence: A Review. Int. J. Inf. Technol. Comput. Sci. 4, 57–68. https://doi.org/10.5815/ijitcs.2012.06.08
- Kusnawi, K., Rahardi, M., Pandiangan, V.D., (2023). Sentiment Analysis of Neobank Digital Banking using Support Vector Machine Algorithm in Indonesia. *JOIV Int. J. Informatics Vis. 7*, 377–383. https://doi.org/10.30630/joiv.7.2.1652
- Kuznetsova, E., Li, Y.-F., Ruiz, C., Zio, E., Ault, G., Bell, K., (2013).

 Reinforcement learning for microgrid energy management.

 Energy 59, 133–146.

 https://doi.org/10.1016/j.energy.2013.05.060
- Lagorse, J., Simoes, M.G., Miraoui, A., (2009). A multiagent fuzzy-logic-based energy management of hybrid systems. *IEEE Trans. Ind.*

- Appl. 45, 2123–2129. https://doi.org/10.1109/TIA.2009.2031786
- Lagouir, M., Badri, A., Sayouti, Y., (2021). Multi-Objective Optimization
 Dispatch Based Energy Management of A Microgrid Running
 Under Grid Connected and Standalone Operation Mode. Int. J.
 Renew. *Energy Dev.* 10, 333–343.
 https://doi.org/10.14710/ijred.2021.34656
- Lahlou, Y., Hajji, A., Aggour, M., (2023). Optimization of a Management Algorithm for an Innovative System of Automatic Switching between Two Photovoltaic and Wind Turbine Modes for an Ecological Production of Green Energy. *Int. J. Renew. Energy Dev.* 12, 36–45. https://doi.org/10.14710/ijred.2023.47137
- Le, A.T., Pandey, A., Sirohi, R., Sharma, P., Chen, W.-H., Pham, N.D.K., Tran, V.D., Nguyen, X.P., Hoang, A.T., (2023). Precise Prediction of Biochar Yield and Proximate Analysis by Modern Machine Learning and SHapley Additive exPlanations. *Energy & Fuels 37*, 17310–17327.

https://doi.org/10.1021/acs.energyfuels.3c02868

- Lee, J., Davari, H., Singh, J., Pandhare, V., (2018). Industrial Artificial Intelligence for industry 4.0-based manufacturing systems.

 Manuf. Lett. 18, 20–23. https://doi.org/10.1016/j.mfglet.2018.09.002
- Li, D., Jayaweera, S.K., (2015). Machine-Learning Aided Optimal Customer Decisions for an Interactive Smart Grid. *IEEE Syst. J.* 9, 1529–1540. https://doi.org/10.1109/JSYST.2014.2334637
- Li, J., Herdem, M.S., Nathwani, J., Wen, J.Z., (2023). Methods and applications for Artificial Intelligence, Big Data, Internet of Things, and Blockchain in smart energy management. *Energy AI* 11, 100208. https://doi.org/10.1016/j.egyai.2022.100208
- Li, X., Zang, C., Liu, W., Zeng, P., Yu, H., (2012). Metropolis Criterion Based Fuzzy Q-Learning Energy Management for Smart Grids. TELKOMNIKA Indones. *J. Electr. Eng. 10*. https://doi.org/10.11591/telkomnika.v10i8.1626
- Lin, H., Sun, K., Tan, Z., Liu, C., Guerrero, J.M., Vasquez, J.C., (2019). Adaptive protection combined with machine learning for microgrids. *IET Gener. Transm. Distrib.* 13, 770–779. https://doi.org/10.1049/iet-gtd.2018.6230
- Liu, B., Kang, J., Jiang, N., Jing, Y., (2011). Cost Control of the Transmission Congestion Management in Electricity Systems Based on Ant Colony Algorithm. *Energy Power Eng. 03*, 17–23. https://doi.org/10.4236/epe.2011.31003
- Liu, H., Chen, C., Lv, X., Wu, X., Liu, M., (2019). Deterministic wind energy forecasting: A review of intelligent predictors and auxiliary methods. *Energy Convers. Manag.* 195, 328–345. https://doi.org/10.1016/j.enconman.2019.05.020
- Liu, H., Mi, X., Li, Y., (2018). Wind speed forecasting method based on deep learning strategy using empirical wavelet transform, long short term memory neural network and Elman neural network. *Energy Convers. Manag.* 156, 498–514. https://doi.org/10.1016/j.enconman.2017.11.053
- Liu, J., Wang, X., Lu, Y., (2017). A novel hybrid methodology for short-term wind power forecasting based on adaptive neuro-fuzzy inference system. *Renew. Energy 103*, 620–629. https://doi.org/10.1016/j.renene.2016.10.074
- Liu, R., Gupta, S., Patel, P., (2023). The Application of the Principles of Responsible AI on Social Media Marketing for Digital Health. *Inf. Syst. Front. 25*, 2275–2299. https://doi.org/10.1007/s10796-021-10191-z
- Liu, S., Henze, G.P., (2006). Experimental analysis of simulated reinforcement learning control for active and passive building thermal storage inventory. *Energy Build.* 38, 148–161. https://doi.org/10.1016/j.enbuild.2005.06.001
- Liu, T., Liu, S., Heng, J., Gao, Y., (2018). A New Hybrid Approach for Wind Speed Forecasting Applying Support Vector Machine with Ensemble Empirical Mode Decomposition and Cuckoo Search Algorithm. Appl. Sci. 8, 1754. https://doi.org/10.3390/app8101754
- Liu, W., Zhuang, P., Liang, H., Peng, J., Huang, Z., (2018). Distributed Economic Dispatch in Microgrids Based on Cooperative Reinforcement Learning. IEEE Trans. Neural Networks Learn. Syst. 29, 2192–2203. https://doi.org/10.1109/TNNLS.2018.2801880
- Logenthiran, T., Srinivasan, D., Khambadkone, A.M., Aung, H.N., (2012). Multiagent System for Real-Time Operation of a

- Microgrid in Real-Time Digital Simulator. *IEEE Trans.* Smart Grid 3, 925–933. https://doi.org/10.1109/TSG.2012.2189028
- Lopes, J.A.P., Hatziargyriou, N., Mutale, J., Djapic, P., Jenkins, N., (2007). Integrating distributed generation into electric power systems: A review of drivers, challenges and opportunities. *Electr. Power Syst. Res.* 77, 1189–1203. https://doi.org/10.1016/j.epsr.2006.08.016
- Louzazni, M., Khouya, A., Amechnoue, K., Gandelli, A., Mussetta, M., Crăciunescu, A., (2018). Metaheuristic Algorithm for Photovoltaic Parameters: Comparative Study and Prediction with a Firefly Algorithm. *Appl. Sci. 8*, 339. https://doi.org/10.3390/app8030339
- Luger, G.F., (2005). Artificial intelligence: structures and strategies for complex problem solving. *Pearson education*.
- Macarulla, M., Casals, M., Forcada, N., Gangolells, M., (2017). Implementation of predictive control in a commercial building energy management system using neural networks. *Energy Build.* 151, 511–519. https://doi.org/10.1016/j.enbuild.2017.06.027
- Mason, K., Grijalva, S., (2019). A review of reinforcement learning for autonomous building energy management. *Comput. Electr. Eng.* 78, 300–312. https://doi.org/10.1016/j.compeleceng.2019.07.019
- MathWorks, n.d. Deep Learning Toolbox Design, train, and analyze deep learning networks [WWW Document].
- Meenal, R., Selvakumar, A.I., (2018). Assessment of SVM, empirical and ANN based solar radiation prediction models with most influencing input parameters. *Renew. Energy 121*, 324–343. https://doi.org/10.1016/J.RENENE.2017.12.005
- Melinda, M., Arnia, F., Yafi, A., Afny, N., Andryani, C., Enriko, I.K.A., (2024). Design and Implementation of Mobile Application for CNN-Based EEG Identification of Autism Spectrum Disorder. *Int. J. Adv. Sci. Eng. Inf. Technol.* 14, 57–64.
- Mnih, V., Kavukcuoglu, K., Silver, D., Rusu, A.A., Veness, J., Bellemare, M.G., Graves, A., Riedmiller, M., Fidjeland, A.K., Ostrovski, G., Petersen, S., Beattie, C., Sadik, A., Antonoglou, I., King, H., Kumaran, D., Wierstra, D., Legg, S., Hassabis, D., (2015). Humanlevel control through deep reinforcement learning. *Nature* 518, 529–533. https://doi.org/10.1038/nature14236
- Moayedi, H., Mehrabi, M., Mosallanezhad, M., Rashid, A.S.A., Pradhan, B., (2019). Modification of landslide susceptibility mapping using optimized PSO-ANN technique. *Eng. Comput. 35*, 967–984. https://doi.org/10.1007/s00366-018-0644-0
- Moayedi, H., Mosavi, A., (2021). An Innovative Metaheuristic Strategy for Solar Energy Management through a Neural Networks Framework. *Energies* 14, 1196. https://doi.org/10.3390/en14041196
- Mocanu, E., Mocanu, D.C., Nguyen, P.H., Liotta, A., Webber, M.E., Gibescu, M., Slootweg, J.G., (2019). On-Line Building Energy Optimization Using Deep Reinforcement Learning. *IEEE Trans. Smart Grid 10*, 3698–3708. https://doi.org/10.1109/TSG.2018.2834219
- Mohamed, A., Mohammed, O., (2013). Real-time energy management scheme for hybrid renewable energy systems in smart grid applications. *Electr. Power Syst. Res.* 96, 133–143. https://doi.org/10.1016/j.epsr.2012.10.015
- Molderink, A., Bakker, V., Bosman, M.G.C., Hurink, J.L., Smit, G.J.M., (2009). Domestic energy management methodology for optimizing efficiency in Smart Grids, in: 2009 IEEE Bucharest PowerTech. *IEEE*, pp. 1–7. https://doi.org/10.1109/PTC.2009.5281849
- Montazeri-Gh, M., Pourbafarani, Z., (2017). Near-Optimal SOC Trajectory for Traffic-Based Adaptive PHEV Control Strategy. *IEEE Trans.* Veh. Technol. *66*, 9753–9760. https://doi.org/10.1109/TVT.2017.2757604
- Mosavi, A., Salimi, M., Ardabili, S.F., Rabczuk, T., Shamshirband, S., Varkonyi-Koczy, A.R., (2019). State of the art of machine learning models in energy systems, a systematic review. *Energies 12*, 1301. https://doi.org/10.3390/en12071301
- Moura, M. das C., Zio, E., Lins, I.D., Droguett, E., (2011). Failure and reliability prediction by support vector machines regression of time series data. *Reliab. Eng. Syst. Saf. 96*, 1527–1534. https://doi.org/10.1016/j.ress.2011.06.006
- Natsheh, E.M., (2013). Hybrid Power Systems Energy Management Based on Artificial Intelligence. PHD Thesis Manchester Metrop.

- Univ.
- Nguyen, H.P., Le, P.Q.H., Pham, V.V., Nguyen, X.P., Balasubramaniam, D., Hoang, A.-T., (2021). Application of the Internet of Things in 3E (efficiency, economy, and environment) factor-based energy management as smart and sustainable strategy. Energy Sources, Part A Recover. *Util. Environ. Eff.* 1–23. https://doi.org/10.1080/15567036.2021.1954110
- Nguyen, H.P., Nguyen, P.Q.P., Nguyen, D.K.P., Bui, V.D., Nguyen, D.T., (2023). Application of IoT Technologies in Seaport Management. JOIV Int. J. Informatics Vis. 7, 228–240. https://doi.org/10.30630/joiv.7.1.1697
- Nguyen, T.T.M., Khoa, P.N.D., Huynh, N.A., (2022). Electrical Energy Management According to Pricing Policy: A Case in Vietnam. *Int. J. Renew. Energy Dev. 11*, 851–862. https://doi.org/10.14710/ijred.2022.46302
- Nguyen, V.G., Rajamohan, S., Rudzki, K., Kozak, J., Sharma, P., Pham, N.D.K., Nguyen, P.Q.P., Xuan, P.N., (2023). Using Artificial Neural Networks for Predicting Ship Fuel Consumption. *Polish Marit*. Res. 30, 39–60. https://doi.org/10.2478/pomr-2023-0020
- Nguyen, V.N., Tarełko, W., Sharma, P., El-Shafay, A.S., Chen, W.-H., Nguyen, P.Q.P., Nguyen, X.P., Hoang, A.T., (2024). Potential of Explainable Artificial Intelligence in Advancing Renewable Energy: Challenges and Prospects. *Energy & Fuels 38*, 1692–1712. https://doi.org/10.1021/acs.energyfuels.3c04343
- Nguyen, X.P., Le, N.D., Pham, V.V., Huynh, T.T., Dong, V.H., Hoang, A.T., (2021). Mission, challenges, and prospects of renewable energy development in Vietnam. *Energy Sources, Part A Recover. Util. Environ. Eff.* 1–13. https://doi.org/10.1080/15567036.2021.1965264
- Nižetić, S., Arıcı, M., Hoang, A.T., (2023). Smart and Sustainable Technologies in Energy Transition. J. Clean. Prod. 135944. https://doi.org/10.1016/j.jclepro.2023.135944
- Novitasari, D.C.R., Fatmawati, F., Hendradi, R., Nariswari, R., Saputra, R.A., (2023). Automated Staging of Diabetic Retinopathy Using Convolutional Support Vector Machine (CSVM) Based on Fundus Image Data. *JOIV Int. J. Informatics Vis.* 7, 2223–2229. https://doi.org/10.30630/joiv.7.4.01501
- Oğcu, G., Demirel, O.F., Zaim, S., (2012). Forecasting Electricity Consumption with Neural Networks and Support Vector Regression. *Procedia - Soc. Behav. Sci.* 58, 1576–1585. https://doi.org/10.1016/j.sbspro.2012.09.1144
- Panait, L., Luke, S., (2005). Cooperative Multi-Agent Learning: The State of the Art. *Auton. Agent. Multi. Agent. Syst.* 11, 387–434. https://doi.org/10.1007/s10458-005-2631-2
- Pang, W.L., Chung, G.C., Chan, K.Y., Ee, L.I., Roslee, M., Fitrey, E., Sim, Y.W., Prasetio, M.D., (2023). Smart Machine Learning-based IoT Health and Cough Monitoring System. *Int. J. Adv. Sci. Eng. Inf. Technol.* 13, 1645–1653. https://doi.org/10.18517/ijaseit.13.5.19024
- Park, S., Lee, J., Bae, S., Hwang, G., Choi, J.K., (2016). Contribution-Based Energy-Trading Mechanism in Microgrids for Future Smart Grid: A Game Theoretic Approach. *IEEE Trans. Ind. Electron.* 63, 4255–4265. https://doi.org/10.1109/TIE.2016.2532842
- Pascual, J., Sanchis, P., Marroyo, L., (2014). Implementation and Control of a Residential Electrothermal Microgrid Based on Renewable Energies, a Hybrid Storage System and Demand Side Management. Energies 7, 210–237. https://doi.org/10.3390/en7010210
- Passino, K.M., Yurkovich, S., Reinfrank, M., (1998). Fuzzy control. Addison-wesley Reading, MA.
- Paudel, S., Elmitri, M., Couturier, S., Nguyen, P.H., Kamphuis, R., Lacarrière, B., Le Corre, O., (2017). A relevant data selection method for energy consumption prediction of low energy building based on support vector machine. *Energy Build. 138*, 240–256. https://doi.org/10.1016/j.enbuild.2016.11.009
- Pérez-Lombard, L., Ortiz, J., Pout, C., (2008). A review on buildings energy consumption information. *Energy Build.* 40, 394–398. https://doi.org/10.1016/j.enbuild.2007.03.007
- Pollet, B.G., Lamb, J.J., (2020). Hydrogen, Biomass and Bioenergy: Integration Pathways for Renewable Energy Applications. Academic Press.
- Prabha, V.L., Monie, E.C., (2007). Hardware Architecture of Reinforcement Learning Scheme for Dynamic Power

- Management in Embedded Systems. EURASIP J. Embed. Syst. 2007, 1–6. https://doi.org/10.1155/2007/65478
- Praseeda, K.I., Reddy, B.V.V., Mani, M., (2016). Embodied and operational energy of urban residential buildings in India. *Energy Build.* 110, 211–219. https://doi.org/10.1016/j.enbuild.2015.09.072
- Prodan, I., Zio, E., (2014). A model predictive control framework for reliable microgrid energy management. *Int. J. Electr. Power Energy Syst.* 61, 399–409. https://doi.org/10.1016/j.ijepes.2014.03.017
- Qu, S., Han, Y., Wu, Z., Raza, H., (2021). Consensus modeling with asymmetric cost based on data-driven robust optimization. Gr. Decis. Negot. 30, 1395–1432.
- Quej, V.H., Almorox, J., Arnaldo, J.A., Saito, L., (2017). ANFIS, SVM and ANN soft-computing techniques to estimate daily global solar radiation in a warm sub-humid environment. *J. Atmos. Solar-Terrestrial Phys.* 155, 62–70. https://doi.org/10.1016/j.jastp.2017.02.002
- Radonjić, A., Pjevčević, D., Maraš, V., (2020). Neural Network Ensemble Approach to Pushed Convoys Dispatching Problems. *Polish Marit. Res.* 27, 70–82. https://doi.org/10.2478/pomr-2020-0008
- Ramesh, T., Prakash, R., Shukla, K.K., (2010). Life cycle energy analysis of buildings: An overview. *Energy Build.* 42, 1592–1600. https://doi.org/10.1016/j.enbuild.2010.05.007
- Ramirez-Sanchez, E., Evangelista-Palma, G., Gutierrez-Navarro, D., Kammen, D.M., Castellanos, S., (2022). Impacts and savings of energy efficiency measures: A case for Mexico's electrical grid. J. Clean. Prod. 340, 130826. https://doi.org/10.1016/j.jclepro.2022.130826
- Rangkuti, A.H., Athalaa, V.H., Indallah, F.H., Febriansyah, F.F., (2023).

 Optimizing Hand Gesture Recognition Using CNN Model Supported by Raspberry pi for Self-Service Technology. *JOIV Int. J. Informatics Vis.* 7, 58–69. https://doi.org/10.30630/joiv.7.1.1032
- Rayati, M., Sheikhi, A., Ranjbar, A.M., (2015). Optimising operational cost of a smart energy hub, the reinforcement learning approach. *Int. J. Parallel, Emergent Distrib. Syst.* 30, 325–341. https://doi.org/10.1080/17445760.2014.974600
- Razak Kaladgi, A., Afzal, A., Manokar, A.M., Thakur, D., Agbulut, U., Alshahrani, S., Saleel C, A., Subbiah, R., (2021). Integrated Taguchi-GRA-RSM optimization and ANN modelling of thermal performance of zinc oxide nanofluids in an automobile radiator. Case Stud. Therm. Eng. 26, 101068. https://doi.org/10.1016/j.csite.2021.101068
- Remani, T., Jasmin, E.A., Ahamed, T.P.I., (2019). Residential Load Scheduling With Renewable Generation in the Smart Grid: A Reinforcement Learning Approach. *IEEE Syst. J. 13*, 3283–3294. https://doi.org/10.1109/JSYST.2018.2855689
- Reymond, M., Patyn, C., Rådulescu, R., Deconinck, G., Nowé, A., (2018).

 Reinforcement learning for demand response of domestic household appliances, in: Proceedings of the Adaptive and Learning Agents Workshop at FAIM.
- Roiné, L., Therani, K., Manjili, Y.S., Jamshidi, M., (2014). Microgrid energy management system using fuzzy logic control, in: 2014 World Automation Congress (WAC). *IEEE*, pp. 462–467.
- Roje, T., Marín, L.G., Sáez, D., Orchard, M., Jiménez-Estévez, G., (2017). Consumption modeling based on Markov chains and Bayesian networks for a demand side management design of isolated microgrids. *Int. J. Energy Res.* 41, 365–376. https://doi.org/10.1002/er.3607
- Rowlands, I.H., WISE, Chai, D.S., Wen, J., Nathwani, J., (2011). Concept Development for Smart Energy Networks.
- Rudzki, K., Gomulka, P., Hoang, A.T., (2022). Optimization Model to Manage Ship Fuel Consumption and Navigation Time. *Polish Marit. Res.* 29, 141–153. https://doi.org/10.2478/pomr-2022-0034
- Rumapea, H., Zarlis, M., Efendy, S., Sihombing, P., (2024). Improving Convective Cloud Classification with Deep Learning: The CC-Unet Model. Int. J. Adv. Sci. Eng. Inf. Technol. 14, 28–36.
- Runge, J., Zmeureanu, R., (2019). Forecasting Energy Use in Buildings Using Artificial Neural Networks: A Review. *Energies 12*, 3254. https://doi.org/10.3390/en12173254
- S, S., Basar, A., Wang, H., (2020). Artificial Neural Network Based Power Management for Smart Street Lighting Systems. *J. Artif. Intell.*

- Capsul. Networks 2, 42–52. https://doi.org/10.36548/jaicn.2020.1.005
- Sai, Z., Lu, C., Jiang, S., Shan, L., James, C., Xiong, N.N., (2020). Energy
 Management Optimization of Open-Pit Mine Solar
 Photothermal-Photoelectric Membrane Distillation Using a
 Support Vector Machine and a Non-Dominated Genetic
 Algorithm. *IEEE Access 8,* 155766–155782.
 https://doi.org/10.1109/ACCESS.2020.3017688
- Said, Z., Sharma, P., Thi Bich Nhuong, Q., Bora, B.J., Lichtfouse, E., Khalid, H.M., Luque, R., Nguyen, X.P., Hoang, A.T., (2023). Intelligent approaches for sustainable management and valorisation of food waste. *Bioresour. Technol.* 377, 128952. https://doi.org/10.1016/j.biortech.2023.128952
- Said, Z., Sharma, P., Tiwari, A.K., Le, V.V., Huang, Z., Bui, V.G., Hoang, A.T., (2022). Application of novel framework based on ensemble boosted regression trees and Gaussian process regression in modelling thermal performance of small-scale Organic Rankine Cycle (ORC) using hybrid nanofluid. *J. Clean. Prod. 360*, 132194. https://doi.org/10.1016/j.jclepro.2022.132194
- Sameti, M., Jokar, M.A., Astaraei, F.R., (2017). Prediction of solar Stirling power generation in smart grid by GA-ANN model. *Int. J. Comput. Appl. Technol.* 55, 147. https://doi.org/10.1504/IJCAT.2017.082860
- Sarwosri, S., Rochimah, S., Laili Yuhana, U., Balqis Hidayat, S., (2023). Software Quality Measurement for Functional Suitability, Performance Efficiency, and Reliability Characteristics Using Analytical Hierarchy Process. *JOIV Int. J. Informatics Vis.* 7, 2421–2426. https://doi.org/10.30630/joiv.7.4.02441
- Seutche, R.V.N., Sawadogo, M., Ngassam, F.N., (2021). Valuation of CO2 Emissions Reduction from Renewable Energy and Energy Efficiency Projects in Africa: A Case Study of Burkina Faso. *Int.* J. Renew. Energy Dev. 10, 713–729. https://doi.org/10.14710/ijred.2021.34566
- Shan, W., Qiao, Z., Heidari, A.A., Chen, H., Turabieh, H., Teng, Y., (2021). Double adaptive weights for stabilization of moth flame optimizer: Balance analysis, engineering cases, and medical diagnosis. *Knowledge-Based Syst. 214*, 106728. https://doi.org/10.1016/j.knosys.2020.106728
- Shao, M., Wang, X., Bu, Z., Chen, X., Wang, Y., (2020). Prediction of energy consumption in hotel buildings via support vector machines. *Sustain. Cities Soc.* 57, 102128. https://doi.org/10.1016/j.scs.2020.102128
- Shao, Z., Zheng, Q., Yang, S., Gao, F., Cheng, M., Zhang, Q., Liu, C., (2020). Modeling and forecasting the electricity clearing price: A novel BELM based pattern classification framework and a comparative analytic study on multi-layer BELM and LSTM. Energy Econ. 86, 104648. https://doi.org/10.1016/j.eneco.2019.104648
- Sharma, P., Sahoo, B.B., Said, Z., Hadiyanto, H., Nguyen, X.P., Nižetić, S., Huang, Z., Hoang, A.T., Li, C., (2023). Application of machine learning and Box-Behnken design in optimizing engine characteristics operated with a dual-fuel mode of algal biodiesel and waste-derived biogas. *Int. J. Hydrogen Energy 48*, 6738–6760. https://doi.org/10.1016/j.ijhydene.2022.04.152
- Sharma, P., Said, Z., Kumar, A., Nižetić, S., Pandey, A., Hoang, A.T., Huang, Z., Afzal, A., Li, C., Le, A.T., Nguyen, X.P., Tran, V.D., (2022a). Recent Advances in Machine Learning Research for Nanofluid-Based Heat Transfer in Renewable Energy System.

 Energy & Fuels 36, 6626–6658. https://doi.org/10.1021/acs.energyfuels.2c01006
- Sharma, P., Said, Z., Memon, S., Elavarasan, R.M., Khalid, M., Nguyen, X.P., Arıcı, M., Hoang, A.T., Nguyen, L.H., (2022b). Comparative evaluation of AI-based intelligent GEP and ANFIS models in prediction of thermophysical properties of Fe3O4-coated MWCNT hybrid nanofluids for potential application in energy systems. *Int. J. Energy Res.* 46, 19242–19257. https://doi.org/10.1002/er.8010
- Shen, L., Chen, H., Yu, Z., Kang, W., Zhang, B., Li, H., Yang, B., Liu, D., (2016). Evolving support vector machines using fruit fly optimization for medical data classification. *Knowledge-Based Syst. 96*, 61–75. https://doi.org/10.1016/j.knosys.2016.01.002
- Shi, W., Li, N., Chu, C.-C., Gadh, R., (2017). Real-Time Energy Management in Microgrids. IEEE Trans. Smart Grid 8, 228–238. https://doi.org/10.1109/TSG.2015.2462294

- Soares, J., Sousa, T., Morais, H., Vale, Z., Faria, P., (2011). An optimal scheduling problem in distribution networks considering V2G, in: 2011 IEEE Symposium on Computational Intelligence Applications In Smart Grid (CIASG). *IEEE*, pp. 1–8. https://doi.org/10.1109/CIASG.2011.5953342
- Sousa, T., Morais, H., Vale, Z., Faria, P., Soares, J., (2012). Intelligent Energy Resource Management Considering Vehicle-to-Grid: A Simulated Annealing Approach. IEEE Trans. Smart Grid 3, 535– 542. https://doi.org/10.1109/TSG.2011.2165303
- Statista, (2019). Global renewable energy industry.
- Statista, (2013). Energy supply, in: OECD Factbook 2013: Economic, *Environmental and Social Statistics*. https://doi.org/10.1787/factbook-2013-41-en
- Sun, M., Zhang, T., Wang, Y., Strbac, G., Kang, C., (2020). Using Bayesian Deep Learning to Capture Uncertainty for Residential Net Load Forecasting. *IEEE Trans.* Power Syst. 35, 188–201. https://doi.org/10.1109/TPWRS.2019.2924294
- Sutton, R.S., Barto, A.G., (2018). Reinforcement learning: An introduction. MIT press.
- Suvon, I.H., Loh, Y.P., Hashim, N., Mohd-Isa, W.N., Ting, C.Y., Ghauth, K.I., Bhattacharijee, A., Matsah, W.R., (2023). Business Category Classification via Indistinctive Satellite Image Analysis Using Deep Learning. Int. J. Adv. Sci. Eng. Inf. Technol. 13, 2219–2230. https://doi.org/10.18517/ijaseit.13.6.19059
- Tabanjat, A., Becherif, M., Hissel, D., Ramadan, H.S., (2018). Energy management hypothesis for hybrid power system of H 2 /WT/PV/GMT via AI techniques. *Int. J. Hydrogen Energy 43*, 3527–3541. https://doi.org/10.1016/j.ijhydene.2017.06.085
- Tan, Y., Liu, W., Qiu, Q., (2009). Adaptive power management using reinforcement learning, in: Proceedings of the 2009 International Conference on Computer-Aided Design. pp. 461–467.
- Tang, L., Zhao, Y., Liu, J., (2014). An Improved Differential Evolution Algorithm for Practical Dynamic Scheduling in Steelmaking-Continuous Casting Production. *IEEE Trans. Evol. Comput.* 18, 209–225. https://doi.org/10.1109/TEVC.2013.2250977
- Tarasiuk, T., Cao, W., Geng, P., Xu, X., (2023). Energy management strategy considering energy storage system degradation for hydrogen fuel cell ship. *Polish Marit. Res.* 30, 95–104. https://doi.org/10.2478/pomr-2023-0025
- Tascikaraoglu, A., Boynuegri, A.R., Uzunoglu, M., (2014). A demand side management strategy based on forecasting of residential renewable sources: A smart home system in Turkey. *Energy Build.* 80, 309–320. https://doi.org/10.1016/j.enbuild.2014.05.042
- Tian, H., Wang, X., Lu, Z., Huang, Y., Tian, G., (2018). Adaptive Fuzzy Logic Energy Management Strategy Based on Reasonable SOC Reference Curve for Online Control of Plug-in Hybrid Electric City Bus. *IEEE Trans. Intell. Transp. Syst.* 19, 1607–1617. https://doi.org/10.1109/TITS.2017.2729621
- Tian, X., Cai, Y., Sun, X., Zhu, Z., Xu, Y., (2019). An adaptive ECMS with driving style recognition for energy optimization of parallel hybrid electric buses. *Energy 189*, 116151. https://doi.org/10.1016/j.energy.2019.116151
- Triandi, B., Efendi, S., Mawengkang, H., Sawaluddin, (2023).

 Regression-based Analytical Approach for Speech Emotion Prediction based on Multivariate Additive Regression Spline (MARS). Int. J. Adv. Sci. Eng. Inf. Technol. 13, 2213–2218. https://doi.org/10.18517/ijaseit.13.6.18603
- Tsui, K.M., Chan, S.C., (2012). Demand Response Optimization for Smart Home Scheduling Under Real-Time Pricing. *IEEE Trans.*Smart Grid 3, 1812–1821. https://doi.org/10.1109/TSG.2012.2218835
- Tu, J., Chen, H., Liu, J., Heidari, A.A., Zhang, X., Wang, M., Ruby, R., Pham, Q.-V., (2021). Evolutionary biogeography-based whale optimization methods with communication structure: Towards measuring the balance. *Knowledge-Based Syst.* 212, 106642. https://doi.org/10.1016/j.knosys.2020.106642
- Tuan Hoang, A., Nižetić, S., Chyuan Ong, H., Tarelko, W., Viet Pham, V., Hieu Le, T., Quang Chau, M., Phuong Nguyen, X., (2021). A review on application of artificial neural network (ANN) for performance and emission characteristics of diesel engine fueled with biodiesel-based fuels. Sustain. Energy Technol. Assessments 47, 101416. https://doi.org/10.1016/j.seta.2021.101416
- Ugwu, J., Odo, K.C., Oluka, L.O., Salami, K.O., (2022). A Systematic

- Review on the Renewable Energy Development, Policies and Challenges in Nigeria with an International Perspective and Public Opinions. *Int. J. Renew. Energy Dev. 11*, 287–308. https://doi.org/10.14710/ijred.2022.40359
- Ullah, Z., Baseer, M., (2022). Operational Planning and Design of Market-Based Virtual Power Plant with High Penetration of Renewable Energy Sources. *Int. J. Renew. Energy Dev. 11*, 620–629. https://doi.org/10.14710/ijred.2022.44586
- Vaisakh, T., Jayabarathi, R., (2022). Analysis on intelligent machine learning enabled with meta-heuristic algorithms for solar irradiance prediction. *Evol. Intell.* 15, 235–254. https://doi.org/10.1007/s12065-020-00505-6
- Vasant, P., Marmolejo, J.A., Litvinchev, I., Aguilar, R.R., (2020). Nature-inspired meta-heuristics approaches for charging plug-in hybrid electric vehicle. *Wirel. Networks* 26, 4753–4766. https://doi.org/10.1007/s11276-019-01993-w
- Venayagamoorthy, G.K., Sharma, R.K., Gautam, P.K., Ahmadi, A., (2016). Dynamic Energy Management System for a Smart Microgrid. *IEEE Trans. Neural Networks Learn. Syst.* 27, 1643– 1656. https://doi.org/10.1109/TNNLS.2016.2514358
- Veza, I., Afzal, A., Mujtaba, M.A., Tuan Hoang, A., Balasubramanian, D., Sekar, M., Fattah, I.M.R., Soudagar, M.E.M., EL-Seesy, A.I., Djamari, D.W., Hananto, A.L., Putra, N.R., Tamaldin, N., (2022a). Review of artificial neural networks for gasoline, diesel and homogeneous charge compression ignition engine. *Alexandria Eng. J.* 61, 8363–8391. https://doi.org/10.1016/j.aej.2022.01.072
- Veza, I., Karaoglan, A.D., Ileri, E., Kaulani, S.A., Tamaldin, N., Latiff, Z.A., Muhamad Said, M.F., Hoang, A.T., Yatish, K.V., Idris, M., (2022b). Grasshopper optimization algorithm for diesel engine fuelled with ethanol-biodiesel-diesel blends. *Case Stud. Therm. Eng. 31*, 101817. https://doi.org/10.1016/j.csite.2022.101817
- Vo, D.T., Nguyen, X.P., Nguyen, T.D., Hidayat, R., Huynh, T.T., Nguyen, D.T., (2021). A review on the internet of thing (IoT) technologies in controlling ocean environment. *Energy Sources, Part A Recover. Util. Environ. Eff.* 1–19. https://doi.org/10.1080/15567036.2021.1960932
- Wang, D., Ge, S., Jia, H., Wang, C., Zhou, Y., Lu, N., Kong, X., (2014). A Demand Response and Battery Storage Coordination Algorithm for Providing Microgrid Tie-Line Smoothing Services. *IEEE Trans. Sustain. Energy 5*, 476–486. https://doi.org/10.1109/TSTE.2013.2293772
- Wang, H., Huang, J., Lin, X., Mohsenian-Rad, H., (2016). Proactive Demand Response for Data Centers: A Win-Win Solution. *IEEE Trans. Smart Grid 7*, 1584–1596. https://doi.org/10.1109/TSG.2015.2501808
- Wang, M., Chen, H., (2020). Chaotic multi-swarm whale optimizer boosted support vector machine for medical diagnosis. Appl. Soft Comput. 88, 105946. https://doi.org/10.1016/j.asoc.2019.105946
- Wang, M., Chen, H., Yang, B., Zhao, X., Hu, L., Cai, Z., Huang, H., Tong, C., (2017). Toward an optimal kernel extreme learning machine using a chaotic moth-flame optimization strategy with applications in medical diagnoses. *Neurocomputing* 267, 69–84. https://doi.org/10.1016/j.neucom.2017.04.060
- Wang, Y., Huang, Z., (2020). Optimization-Based Energy Management Strategy for a 48-V Mild Parallel Hybrid Electric Power System. *J. Energy Resour. Technol.* 142. https://doi.org/10.1115/1.4045866
- Wasista, S., Tjandrasa, H., Djanali, S., (2023). Design an Intelligent Balanced Control of Quadruped Legs Based on Adaptive Neuro-Fuzzy Inference System (ANFIS). Int. J. Adv. Sci. Eng. Inf. Technol. 13, 901–910. https://doi.org/10.18517/ijaseit.13.3.18589
- Wattana, B., Aungyut, P., (2022). Impacts of Solar Electricity Generation on the Thai Electricity Industry. *Int. J. Renew. Energy Dev. 11*, 157–163. https://doi.org/10.14710/ijred.2022.41059
- Wedashwara, W., Yadnya, M.S., Sudiarta, I.W., Arimbawa, I.W.A., Mulyana, T., (2023). Solar Powered Vibration Propagation Analysis System using nRF24l01 based WSN and FRBR. JOIV Int. J. Informatics Vis. 7, 15–21. https://doi.org/10.30630/joiv.7.1.1592
- Wei, Q., Liu, D., Shi, G., (2015). A novel dual iterative Q-learning method for optimal battery management in smart residential environments. IEEE Trans. Ind. Electron. 62, 2509–2518.

https://doi.org/10.1109/TIE.2014.2361485

- Wei, T., Wang, Y., Zhu, Q., (2017). Deep Reinforcement Learning for Building HVAC Control, in: Proceedings of the 54th Annual Design Automation Conference 2017. ACM, New York, NY, USA, pp. 1–6. https://doi.org/10.1145/3061639.3062224
- Wen, Z., O'Neill, D., Maei, H., (2015). Optimal Demand Response Using Device-Based Reinforcement Learning. *IEEE Trans. Smart Grid 6*, 2312–2324. https://doi.org/10.1109/TSG.2015.2396993
- Whitehead, B., Andrews, D., Shah, A., Maidment, G., (2015). Assessing the environmental impact of data centres part 2: Building environmental assessment methods and life cycle assessment. Build. *Environ.* 93, 395–405. https://doi.org/10.1016/j.buildenv.2014.08.015
- Witkowska, A., Rynkiewicz, T.N., (2018). Dynamically Positioned Ship Steering Making Use of Backstepping Method and Artificial Neural Networks. *Polish Marit. Res.* 25, 5–12. https://doi.org/10.2478/pomr-2018-0126
- Wu, C.-H., Ho, J.-M., Lee, D.T., (2004). Travel-Time Prediction With Support Vector Regression. *IEEE Trans. Intell. Transp. Syst. 5*, 276–281. https://doi.org/10.1109/TITS.2004.837813
- Xiao, F., Fan, C., (2014). Data mining in building automation system for improving building operational performance. *Energy Build.* 75, 109–118. https://doi.org/10.1016/j.enbuild.2014.02.005
- Xie, S., Hu, X., Qi, S., Lang, K., (2018). An artificial neural networkenhanced energy management strategy for plug-in hybrid electric vehicles. *Energy 163*, 837–848. https://doi.org/10.1016/j.energy.2018.08.139
- Xin, L., Chuanzhi, Z., Peng, Z., Haibin, Y., (2012). Genetic based fuzzy Q-learning energy management for smart grid, in: Proceedings of the 31st Chinese Control Conference. *IEEE*, pp. 6924–6927.
- Xu, X., Chen, H., (2014). Adaptive computational chemotaxis based on field in bacterial foraging optimization. Soft Comput. 18, 797–807. https://doi.org/10.1007/s00500-013-1089-4
- Xu, Y., Chen, H., Luo, J., Zhang, Q., Jiao, S., Zhang, X., (2019). Enhanced Moth-flame optimizer with mutation strategy for global optimization. *Inf. Sci.* (Ny). 492, 181–203. https://doi.org/10.1016/j.ins.2019.04.022
- Yacim, J.A., Boshoff, D.G.B., (2020). Neural networks support vector machine for mass appraisal of properties. *Prop. Manag. 38*, 241– 272. https://doi.org/10.1108/PM-09-2019-0053
- Yadav, A.K., Malik, H., Chandel, S.S., (2015). Application of rapid miner in ANN based prediction of solar radiation for assessment of solar energy resource potential of 76 sites in Northwestern India. Renew. Sustain. Energy Rev. 52, 1093–1106. https://doi.org/10.1016/j.rser.2015.07.156
- Yaïci, W., Longo, M., Entchev, E., Foiadelli, F., (2017). Simulation Study on the Effect of Reduced Inputs of Artificial Neural Networks on the Predictive Performance of the Solar Energy System. Sustainability 9, 1382. https://doi.org/10.3390/su9081382
- Yan, J., Menghwar, M., Asghar, E., Kumar Panjwani, M., Liu, Y., (2019). Real-time energy management for a smart-community microgrid with battery swapping and renewables. *Appl. Energy 238*, 180–194. https://doi.org/10.1016/j.apenergy.2018.12.078
- Yan, T., Liu, J., Niu, Q., Chen, J., Xu, S., Niu, M., Lin, J.Y.S., (2020a). Distributed energy storage node controller and control strategy based on energy storage cloud platform architecture. Glob. Energy Interconnect. 3, 166–174. https://doi.org/10.1016/j.gloei.2020.05.008
- Yan, T., Liu, J., Niu, Q., Chen, J., Xu, S., Niu, M., Lin, J.Y.S., (2020b). Distributed energy storage node controller and control strategy based on energy storage cloud platform architecture. Glob. Energy Interconnect. 3, 166–174. https://doi.org/10.1016/j.gloei.2020.05.008
- Yavasoglu, H.A., Tetik, Y.E., Ozcan, H.G., (2020a). Neural network-based energy management of multi-source (battery/UC/FC) powered electric vehicle. *Int. J. Energy Res.* 44, 12416–12429. https://doi.org/10.1002/er.5429
- Yavasoglu, H.A., Tetik, Y.E., Ozcan, H.G., (2020b). Neural network-based energy management of multi-source (battery/UC/FC) powered electric vehicle. *Int. J. Energy Res.* 44, 12416–12429. https://doi.org/10.1002/er.5429
- Yazdanian, M., Mehrizi-Sani, A., (2014). Distributed Control Techniques in Microgrids. *IEEE Trans. Smart Grid 5*, 2901–2909. https://doi.org/10.1109/TSG.2014.2337838

- Yousefi, S., Moghaddam, M.P., Majd, V.J., (2011). Optimal real time pricing in an agent-based retail market using a comprehensive demand response model. *Energy 36*, 5716–5727. https://doi.org/10.1016/j.energy.2011.06.045
- Yu, C., Chen, M., Cheng, K., Zhao, X., Ma, C., Kuang, F., Chen, H., (2022). SGOA: annealing-behaved grasshopper optimizer for global tasks. *Eng. Comput.* 38, 3761–3788. https://doi.org/10.1007/s00366-020-01234-1
- Yuan, R., Li, Z., Guan, X., Xu, L., (2010). An SVM-based machine learning method for accurate internet traffic classification. *Inf. Syst. Front.* 12, 149–156. https://doi.org/10.1007/s10796-008-9131-2
- Yunidar, Y., Melinda, M., (2023). Position and Temperature Detector for Autism Spectrum Disorder Children based on Sensor and Using IoT System. *Int. J. Adv. Sci. Eng. Inf. Technol. 13*, 2105–2111. https://doi.org/10.18517/ijaseit.13.6.19416
- Zadeh, L.A., (1965). Fuzzy sets. *Inf. Control 8*, 338–353. https://doi.org/10.1016/S0019-9958(65)90241-X
- Zafar, A., Shah, S., Khalid, R., Hussain, S.M., Rahim, H., Javaid, N., (2017). A Meta-Heuristic Home Energy Management System, in: 2017 31st International Conference on Advanced Information Networking and Applications Workshops (WAINA). *IEEE*, pp. 244–250. https://doi.org/10.1109/WAINA.2017.118
- Zaki, M., (2024). Effectiveness of Vehicular Communication Using NP-CSMA with Bernoulli-Based Gaussian Interpolation Function. Int. J. Adv. Sci. Eng. Inf. Technol. 14, 89–98.
- Zendehboudi, A., Baseer, M.A., Saidur, R., (2018). Application of support vector machine models for forecasting solar and wind energy resources: A review. *J. Clean. Prod.* 199, 272–285. https://doi.org/10.1016/j.jclepro.2018.07.164
- Zeng, P., Li, H., He, H., Li, S., (2019). Dynamic Energy Management of a Microgrid Using Approximate Dynamic Programming and Deep Recurrent Neural Network Learning. *IEEE Trans. Smart Grid* 10, 4435–4445. https://doi.org/10.1109/TSG.2018.2859821
- Zhang, A., Zhang, P., Feng, Y., (2019). Short-term load forecasting for microgrids based on DA-SVM. COMPEL Int. J. Comput. Math. Electr. Electron. Eng. 38, 68–80. https://doi.org/10.1108/COMPEL-05-2018-0221
- Zhang, G., Sun, H., (2016). Secure Distributed Detection under Energy Constraint in IoT-Oriented Sensor Networks. *Sensors 16*, 2152. https://doi.org/10.3390/s16122152
- Zhang, L., Qiu, Y., Chen, Y., Hoang, A.T., (2023). Multi-objective particle swarm optimization applied to a solar-geothermal system for electricity and hydrogen production; Utilization of zeotropic mixtures for performance improvement. *Process Saf. Environ. Prot. 175*, 814–833. https://doi.org/10.1016/j.psep.2023.05.082
- Zhang, Y., Liu, R., Wang, X., Chen, H., Li, C., (2021). Boosted binary Harris hawks optimizer and feature selection. *Eng. Comput. 37*, 3741–3770. https://doi.org/10.1007/s00366-020-01028-5
- Zhang, Y., Salem, M., Elmasry, Y., Hoang, A.T., Galal, A.M., Pham Nguyen, D.K., Wae-hayee, M., (2022). Triple-objective optimization and electrochemical/technical/environmental study of biomass gasification process for a novel high-temperature fuel cell/electrolyzer/desalination scheme. *Renew. Energy* 201, 379–399. https://doi.org/10.1016/j.renene.2022.10.059
- Zhao, X., Zhang, X., Cai, Z., Tian, X., Wang, X., Huang, Y., Chen, H., Hu, L., (2019). Chaos enhanced grey wolf optimization wrapped ELM for diagnosis of paraquat-poisoned patients. *Comput. Biol. Chem.* 78, 481–490. https://doi.org/10.1016/j.compbiolchem.2018.11.017
- Zhao, Y., Moayedi, H., Bahiraei, M., Foong, L.K., (2020). Employing TLBO and SCE for optimal prediction of the compressive strength of concrete. Smart Struct. Syst. 26, 753–763.
- Zheng Chen, Mi, C.C., Jun Xu, Xianzhi Gong, Chenwen You, (2014).

 Energy Management for a Power-Split Plug-in Hybrid Electric Vehicle Based on Dynamic Programming and Neural Networks.

 IEEE Trans. Veh. Technol. 63, 1567–1580. https://doi.org/10.1109/TVT.2013.2287102
- Zhu, M., (2021). Implementation of support-vector machine algorithm to develop a model for electronic commerce energy regulatory system. *Energy Reports* 7, 2703–2710. https://doi.org/10.1016/j.egyr.2021.05.009

Zhu, W., Hou, Y., Wang, E., Wang, Y., (2020). Design of Geographic Information Visualization System for Marine Tourism Based on Data Mining. *J. Coast. Res.* 103, 1034. https://doi.org/10.2112/SI103-215.1

Zhuang Zhao, Won Cheol Lee, Yoan Shin, Kyung-Bin Song, (2013). An Optimal Power Scheduling Method for Demand Response in Home Energy Management System. *IEEE Trans. Smart Grid 4*, 1391–1400. https://doi.org/10.1109/TSG.2013.2251018



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