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Review Artificial Intelligence Applications in Renewable Energy Systems Integration

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Abstract: - The transition to renewable energy (RE) sources is critical for addressing global energy demands and environmental concerns. This review paper focuses on the pivotal role of Machine Learning (ML) and Deep Learning (DL) in optimizing and predicting the performance of RE systems, particularly solar and wind power. We explore various applications of these advanced technologies in forecasting energy demand and consumption, predicting the output power of renewable systems, and optimizing the operation and maintenance of these systems. The paper also delves into the significance of Explainable AI (XAI) in enhancing the transparency and understandability of AI models in energy applications. Our comprehensive analysis reveals that while ML and DL offer transformative potential in the RE sector, challenges such as data complexity, system integration, and model interpretability remain. Concluding, this work aims to provide a foundation for future research and development in this rapidly evolving field, asserting that the continued advancement and integration of AI technologies in RE systems is essential for achieving a sustainable and efficient energy future.

Keywords: *Solar Energy, Wind Energy, Deep learning, Machine learning, Optimization*.

I. INTRODUCTION

RE systems, particularly those focused on electricity generation, are increasingly adopted in various advanced and emerging economies. This uptick in usage is driven by concerns about energy stability, environmental changes, and the need to address air pollution [1, 2, 3]. The promise of achieving energy independence, reducing greenhouse gases, and improving air quality are strong motivators for the shift towards RE sources [4, 5]. However, it's important for policymakers to also consider the broader economic impacts of these new technologies [6]. In recent years, there's been a significant focus on the job creation potential of these RE systems, attracting interest from a diverse group of professionals from industry, academia, engineering, government, civil society, and private sectors [7, 8, 9, 10]. Particularly, wind and solar energy (SE) generation methods have gained both local and global attention due to the increasing concerns about the sustainability of nuclear and fossil fuel sources [11, 12, 13]. The main drivers for adopting wind and solar technologies include environmental benefits like reduced carbon emissions, lower capital investment requirements, diversification of fuel sources, energy independence, improved energy efficiency, and the potential for enhancing power quality and reliability. In some cases, these technologies can also defer the need for grid expansion by generating power closer to where it's needed [14]. However, there are challenges to address: the variability of wind and solar power generation, the precision of forecasting, geographical disparities in resource availability, and the need for additional investment to integrate these intermittent sources into the power grid effectively [15, 16]. For example, California's energy plan aims to source 33% of its energy needs from renewable sources by 2020, with a significant portion expected to come from wind and solar [17]. Addressing these challenges requires innovative solutions, often utilizing optimization and AI methods to analyze and solve complex parameters [18, 19, 20, 2, 22]. Other concerns include the availability and quality of power, resource location, and cost issues.

In numerous countries around the world, access to electricity remains a significant challenge, with some areas having no power generation or experiencing weak power supply [23]. This issue of energy accessibility is a major concern across various nations. One of the lowest recorded power consumption rates globally is just 208 kWh per capita [24]. Looking at the electricity production data from 2010 the total generation capacity was 5823 MGW, with a vast majority, 96.05%, coming from thermal sources, and the remainder being hydroelectric [24]. RE sources, which are becoming increasingly important, include Solar, PV, Wind, biomass, and geothermal energy [25]. Given this context, it becomes strategically essential to explore if alternative energy sources like Wind and Solar can meet

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a portion of Bangladesh's energy needs in a cost-effective manner [26]. The prediction of power generation is a vital and economically savvy approach for integrating renewable sources like Solar and Wind into electrical grids [27]. While forecasting for green energy, particularly for large-scale producers, is a standard practice in the power industry, solar power forecasting, especially for distributed Solar and PV systems, is relatively new and poses unique challenges. Accurate forecasting is possible by leveraging real-time metrics and detailed static data. [28].

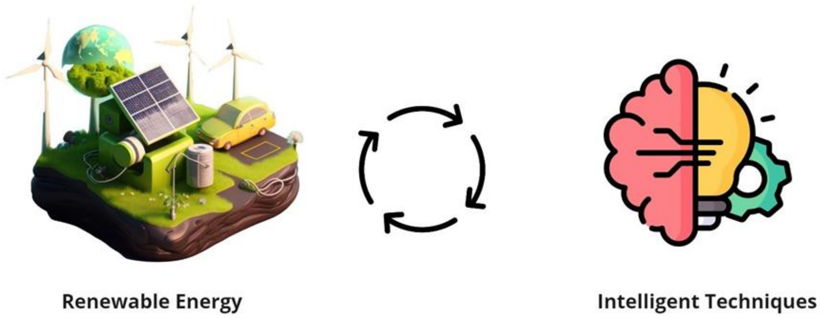

Fig. 1: Renewable energy and intelligent Techniques

This paper aims to address the gap in comprehensive understanding and critical analysis of the integration of renewable energy systems, particularly solar and wind power, into the existing energy infrastructure. Motivated by the urgent need to transition to sustainable energy sources, our work delves into the intricate challenges and opportunities presented by these technologies. We critically evaluate the economic, environmental, and technical aspects of renewable energy adoption, emphasizing the role of advanced technologies like AI and ML in enhancing efficiency and reliability. Our contribution lies in providing a detailed assessment of current methodologies and practices, identifying key areas for improvement, and proposing innovative solutions for more effective integration of renewable energy sources. By doing so, we offer a clearer, more nuanced per- spective that is vital for policymakers, industry professionals, and researchers in making informed decisions and fostering the growth of renewable energy globally. This paper serves as a compre- hensive resource for understanding the current landscape of renewable energy, its challenges, and the potential pathways to overcome these obstacles for a sustainable future.

II. Energy Consumption and Demand Forecast

A. Machine Learning and deep learning overview

Machine learning and deep learning, two key components in the field of artificial intelligence, have gained substantial momentum in recent years. Their evolution has been significantly in- fluenced by the widespread availability of vast datasets and the advancements in computational capabilities. These technologies are now integral in various sectors like healthcare, finance, and retail, reshaping how these industries operate. This article seeks to offer a detailed exploration of machine learning and deep learning, highlighting their distinctions and similarities. It will delve into the specific methodologies employed in each area—machine learning harnessing sta- tistical techniques and deep learning utilizing neural networks for handling large data volumes. Furthermore, the article will examine the diverse applications of these technologies across dif- ferent industries and assess their societal impacts. This comprehensive analysis aims to provide readers with a clear understanding of the capabilities and limitations of machine learning and deep learning [29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44]. The rapid evolu- tion of artificial intelligence has been significantly propelled by the rise of machine learning and deep learning technologies. Known for their proficiency in analyzing extensive datasets, making predictions, and unlocking new insights, these technologies are at the forefront of a data-driven revolution. With the continuous growth of data generation and the advancements in computational power, the transformative potential of machine learning and deep learning in various industries is becoming increasingly evident. This article aims to offer a comprehensive exploration of these technologies, delving into their applications and societal impacts. It will cover the fundamental principles of machine learning and deep learning, differentiate between the two, and showcase their diverse applications, thus illuminating the immense possibilities they hold for the future [45, 46, 47, 48, 49, 50, 51, 52, 53, 54].

Machine learning and deep learning have catalyzed significant breakthroughs in research and innovation, particularly in sectors like healthcare, finance, and transportation. Their capability to process and analyze large datasets has already manifested in advancements in areas such as medical imaging analysis, natural language processing, speech recognition, and autonomous vehicles. These technologies are pivotal in understanding complex systems, aiding in decision-making, and devising efficient solutions to real-world challenges [55, 56, 57, 58, 59, 60]. While machine learning and deep learning are often mentioned interchangeably, they represent distinct facets of artificial intelligence. Machine learning is centered around algorithms that learn from data autonomously, without explicit programming. In contrast, deep learning, a subset of machine learning, leverages neural networks to mimic the human brain's structure and function. These neural networks excel at learning from unstructured data, making them particularly effective in complex tasks like image and speech recognition [61, 62, 63, 64, 65, 66, 67]. Despite their transformative potential, machine learning and deep learning are still in devel- opmental phases. Ongoing research and innovation are crucial to fully harness their capabilities and address challenges such as bias and data privacy. Nevertheless, the future looks promis- ing for these technologies, with continuous advancements and discoveries driving their evolution [68, 69, 70, 71, 72, 73, 74, 75].

In this review, we critically analyze the specific roles and impacts of ML and DL in enhanc- ing the efficiency and predictability of RE systems, focusing on solar and wind power. While ML and DL have shown significant promise in various sectors, their application in RE systems presents unique challenges and opportunities. We delve into how ML algorithms can optimize en- ergy production and distribution by accurately predicting solar and wind power outputs, thereby addressing intermittency issues inherent in these energy sources. Similarly, DL's advanced neural networks are crucial for processing vast amounts of unstructured data from weather patterns and energy consumption trends to improve forecasting accuracy and system reliability. However, this paper also brings to light the limitations and challenges faced in this domain, such as the need for large, high-quality datasets, the risk of model overfitting, and the complexity of integrating these AI technologies into existing energy infrastructures. Additionally, we explore the ethical consider- ations, including data privacy and bias in algorithmic decision-making, that must be navigated to effectively implement ML and DL in RE systems. Through this critical analysis, we aim to provide a comprehensive understanding of how ML and DL can be strategically employed to advance solar and wind energy technologies, paving the way for a more sustainable and efficient energy future.

B. Forecasting related works

In the realm of energy systems (ES), ML and DL are extensively utilized for forecasting purposes. Applications [76, 77, 78]. A significant portion of the global energy consumption and waste is attributed to buildings, making the reduction of energy usage in these structures crucial for mitigating climate change impacts [79]. Consequently, a considerable amount of research focuses on predicting energy consumption and demand in buildings. The forecasting methodologies in this field are generally divided into three time horizons [80]. These predictions are vital at various scales, from individual households to national levels. Effective control and optimization of device performance not only aid in balancing supply and demand, particularly in the context of nearly zero-energy buildings, but also assist in planning and reducing costs in ESs [81]. Accurate information regarding residents' electricity consumption is essential for enhancing load forecasting precision, ensuring stable power system operations, and facilitating energy management and planning [82]. In the field of ESs, recent research has focused on the use of ML and DL for predicting building energy consumption. Amasyali et al. conducted a comprehensive review of these methods, noting a predominance of studies on commercial and educational buildings with a focus on short-term forecasts. The study highlighted that while ML-based models generally perform well, each has its unique strengths and weaknesses, making them suitable for specific applications [83]. Deb et al. reviewed nine Time Series (TS) forecasting techniques in the context of building energy consumption. This paper made qualitative and quantitative comparisons of these techniques and emphasized the effectiveness of HMs, which combine different forecasting methods. One key finding is the potential of integrating TS prediction techniques with optimization methods [84]. Walker et al. employed ML algorithms like Boosted for hourly electricity demand prediction in commercial buildings. Their study found that the Random Forest model outperformed others in terms of accuracy (ACC) and prediction error [85]. Grimaldo et al. combined the k Nearest Neighbor algorithm with visual analytics for energy supply and demand prediction. This approach provided accurate results and allowed users to explore various forecasting scenarios and understand consumption and production patterns [86]. Liu et al. evaluated the effectiveness of the SVM algorithm in predicting energy consumption and identifying consumption patterns in public buildings. The study found SVM to be accurate and effective in distinguishing normal from abnormal energy consumption patterns [87].

Kaytez et al. utilized ARIMA and Least Square SVM to develop a Hybrid Model for predicting long-term power consumption in Turkey's grid. Comparisons with Multiple Linear Regression and single ARIMA models showed this HM to have better ACC and prediction error rates [88]. Fan et al. introduced an innovative Hybrid Model. This model, tested with data from an Australian city, outperformed others though it had limitations in runtime performance [89]. Jamil et al. implemented an ARIMA model to predict power consumption in Pakistani hydropower plants, aiding in future energy supply, demand management, and planning. The model's strong performance was validated against real data and used to forecast hydropower consumption up to 2030 [90]. Beyca et al. analyzed natural gas consumption forecasting in a Turkish province. The study found SVR to be more accurate than the other two models, providing valuable insights for developing countries with similar consumption patterns and consumer behaviors [91]. Wen et al. introduced a DL method, this model effectively compensating for missing data by learning from historical patterns [92]. Hagh et al. proposed a hybrid model combining SVM with faster clustering and Artificial NN to predict home appliance power consumption and peak customer demand. Their model achieved a high ACC of 99.2%, demonstrating its effectiveness with smart meter data [93]. Hafeez et al. introduced an innovative hybrid model for short-term electrical load prediction, incorporating Modified Mutual Information, a Deep Learning model called Factored Conditional Restricted Boltzmann Machine, and an optimization model named Genetic Wind-Driven Optimization. Compared to other models like ANN and LSTM, their approach showed superior performance in ACC, average runtime, and convergence rate [94]. Khan et al. developed a CSNN, integrating Cuckoo Search (CS) with ANN, enhancing ACC, convergence time, and compatibility for fore- casting power consumption in OPEC countries. This model outperformed others like Accelerated Particle Swarm Optimization Neural Network, Genetic Algorithm Neural Network, and Artificial Bee Colony Neural Network, proving more efficient and compatible with recent algorithms [95]. Kazemzadeh et al. proposed a HM for long-term prediction of peak electrical load and total demand. This HM demonstrated superior performance compared to the individual models of PSO-SVR, ANN, and ARIMA [96]. Fathi et al. reviewed energy performance prediction in urban buildings, considering building types, energy types, and forecasting horizons. This review highlighted ANN and SVR as the most frequently used algorithms for predicting buildings' energy performance, particularly focusing on electrical energy consumption [97]. Table 1 provided detailed summary of ML and DL.

Table 1: Summary of ML and DL Techniques in Energy Consumption and Demand Forecasting

Authors	**Model/Method Used**	**Application**	**Key Findings**
Amasyali et al. [83]	Various ML methods	Building energy consumption	Focus on short-term forecasts in commercial and educational buildings.
Deb et al. [84]	TS forecasting techniques (e.g.,Fuzzy Logic, SVM)	Building energy consumption	Hybrid Models combining different forecasting methods are effective.
Walker et al. [85]	Boosted-Tree, Random Forest, SVM,ANN	Hourly electricity demand in commercial buildings	Random Forest outperforms in ACC and prediction error.
Grimaldo et al. [86]	k Nearest Neighbor with visual analytics	Energy supply and demand prediction	Accurate results; useful for exploring forecasting scenarios.
Hagh et al. [93]	Hybrid SVM and ANN	Home appliance power consumption	High ACC (99.2%) with smart meter data.
Hafeez et al. [94]	Hybrid model (MMI, Factored CRBM, GWDO)	Short-term electrical load prediction	Superior in ACC, runtime, and convergence rate.

Khan et al.	CSNN	Power consumption in OPEC countries	Outperforms in ACC, convergence time, and compatibility.
Kazemzadeh et al. [96]	Hybrid Model (ARIMA, ANN,PSO-SVR)	Long-term load demand prediction	Superior to individual models.
Fathi et al. [97]	Review (ANN and SVR)	Energy performance in urban buildings	Frequently used for predicting building energy performance.
Liu et al. [87]	SVM	Energy consumption in public buildings	Effective in distinguishing consumption patterns.
Kaytez et al. [88]	Hybrid Model (ARIMA, LS-SVM)	Long-term power consumption in Turkey	Better ACC than MLR and single ARIMA.
Fan et al. [89]	EMD-SVR-PSO-AR-GARCH Hybrid Model	Power consumption forecasting	Outperforms others but limited in runtime performance.
Jamil et al. [90]	ARIMA	Hydropower consumption in Pakistan	Strong performance, used for forecasting up to 2030.
Beyca et al. [91]	MLR, SVR, ANN	Natural gas consumption in Turkey	SVR is more accurate for developing countries.
Wen et al. [92]	DRNN-GRU	Short-term residential load demandforecasting	Surpasses traditional methods in ACC.

III. Predicting Solar Systems

With the rise of Solar Energy (SE), the need for accurately predicting the output power of solar systems has become increasingly crucial. The growing installed capacity of Photovoltaic Solar Energy (PV SE) necessitates reliable forecasting methods due to the inherently variable nature of SE [98, 99]. Traditional models often struggle with the complexity of Solar Radiation (SR) data, leading to a shift towards Machine Learning (ML)-based models for more accurate predictions [100, 101]. These models take into account a variety of factors such as cell position, solar cell type, and weather conditions, underlining the critical role of SR data in forecasting [102]. A study by Voyant et al. evaluated different ML methods for predicting SR, focusing on Neural Networks (NN) and Support Vector Regression (SVR), while also exploring methods like k-Nearest Neighbors (kNN) and Random Forest (RF). The study suggested that Hybrid Models, combining different ML techniques, could further enhance prediction performance [103]. Similarly, Huertas et al. explored four models, finding that a hybrid model with SVM outperformed single predictor models [104].

In a case study by Govindasamy et al. conducted in South Africa, various algorithms such as ANN, SVR, General Regression Neural Network, and RF were used to assess the impact of PM10 air pollution on SR. The ANN algorithm was found to be superior in terms of ACC and computational efficiency [105]. Gürel et al. compared an experimental model, ANN, Time Series, and a mathematical model using various climatic data, concluding that the ANN algorithm was most accurate for evaluating SR [106]. Alizamir et al. compared six ML-based models in the United States and Turkey for SR predic- tion. The Gradient Boosting Tree model emerged as the most effective, outperforming others in terms of error rates and ACC [107]. Srivastava et al. reviewed four ML algorithms for predicting hourly SR, with the RF model deemed most effective and the CART as the least [108]. Benali et al. compared three models for hourly SR prediction, finding the RF model to be the most accurate, especially in winter and summer, while spring and autumn predictions posed more challenges due to diverse SR patterns [109]. In a study by Ağbulut et al., four ML algorithms and DL were employed to predict daily SR, using data like daily temperature extremes, cloud cover, and extraterrestrial SR. While all algorithms were effective, the ANN algorithm outperformed others, with kNN being the least effective [110].

These studies collectively underscore the diverse methodologies and effectiveness of various ML and DL approaches in predicting solar radiation. However, a critical analysis reveals that while these models offer significant improvements over traditional methods, challenges such as data quality, model complexity, and computational demands persist. The varied performance across different geographic locations and seasons also highlights the necessity for tailored approaches. Future research should focus on refining these models, considering local environmental conditions and integrating real-time data for more accurate and robust predictions. Summary of ML and DL Techniques in Predicting Solar System Output Power is shown in Table 2.

Table 2: Summary of ML and DL Techniques in Predicting Solar System Output Power

Authors	**Models/Methods Used**	**Application**	**Key Findings**
Voyant et al. [103]	NN, Support Vec- tor Regression, kNN, Random Forest	Predicting SR	Hybrid Models may enhance pre-diction performance.
Huertas et al. [104]	Smart Persistence, Satellite imagery,NWP, HybridSatellite-NWP with SVM	SR predictions	Hybrid model with SVM outper- forms single predictor models.
Govindasamy et al. [105]	ANN, SVR, Gen- eral Regression Neural Network, Random Forest	Impact of PM10 air pollution on SR	ANN superior in ACC and com- putational efficiency.
Gürel et al. [106]	Experimental model, ANN, Time Series, Mathemati- cal model	Evaluating SR	ANN algorithm most accurate with climatic data.
Alizamir et al. [107]	Six ML-based mod- els including Gradi-ent Boosting Tree	SR prediction in US and Turkey	Gradient Boosting Tree most ef- fective in error rates and ACC.
Srivastava et al. [108]	MARS, CART, M5, RF	Predicting hourly SR	RF most effective, CART least effective.
Benali et al. [109]	ANN, RF, Smart Persistence	Hourly SR predic- tion	RF most accurate, especially in winter and summer.
Ağbulut et al. [110]	SVM, ANN, kNN, DL	Daily SR prediction	ANN outperforms others, kNN least effective.

IV. Predicting Wind Systems

The wind energy sector's rapid growth can be attributed to the clean, inexpensive, and abundant nature of wind resources. However, the challenge in wind energy prediction stems from its nonlinear and random characteristics, posing difficulties in maintaining consistent power generation [111, 112]. In Europe, a notable shift towards offshore wind farms has been observed, offering advantages like abundant wind resources and larger generation capacities [113]. Zendehboud et al. conducted a comparative study favoring the SVM model over others, such as the ANN, for WP prediction. They proposed hybrid SVM models to enhance ACC, indicating a potential direction for future research in this area [114]. Wang et al. emphasized the challenges of using a single model for WS prediction across different regions. They advocated for a more flexible approach that could adapt to regional variations, thereby improving forecast accuracy and providing more probabilistic information [115]. In their study, Demolli et al. employed five ML algorithms, finding that XGBoost, Support Vector Regression (SVR), and Random Forest were particularly effective, with RF emerging as the top performer. The study also noted the unique effectiveness of the SVR algorithm when standard deviation was excluded from the data, highlighting the sensitivity of ML models to input features. Furthermore, the adaptability of these ML models to new geographical locations was a significant finding, suggesting their broad applicability [116]. Xiao et al. introduced a self-adaptive Kernel Extreme Learning Machine (KELM), addressing the need for continual retraining of ANN models with updated data. This model's efficiency in incorporating new information while retaining relevant old data marks a significant advancement in training efficiency, reducing retraining costs, and improving forecasting accuracy [117]. Cadenas et al. compared the ARIMA and NARX models for WS prediction. The study found that the NARX model exhibited less error compared to ARIMA, suggesting its potential superiority in certain contexts [118].

Further contributions to WP prediction include Li et al.'s use of the Improved Dragonfly Algorithm-based SVM for short-term WP forecasting [119], Tian et al.'s application for WS fore- casting [120], and Hong et al.'s deployment of the Convolutional Neural Network (CNN) model for next-day WS prediction [121]. Collectively, these studies underscore the diversity and complexity of ML and DL methodologies in wind energy prediction. However, a critical analysis reveals that the choice of model and its effectiveness significantly depend on the specific characteristics of the dataset and the geographical location. While advancements like the self-adaptive KELM show promise in addressing the challenges of model retraining, there remains a need for ongoing research to improve model accuracy, computational efficiency, and adaptability to varying environmental conditions. This review highlights the necessity for continuous innovation in ML and DL techniques to ensure reliable and efficient wind energy forecasting. The Summary of ML and DL Techniques in Predicting Wind System Output Power is shown in Table 3.

Table 3: Summary of ML and DL Techniques in Predicting Wind System Output Power

Authors	**Models/Methods Used**	**Application**	**Key Findings**
Zendehboud et al. [114]	SVM	WP prediction	Favoring SVM for its speed, reli-ability, and ACC; suggestion forhybrid models.
Wang et al. [115]	Hybrid Model (EWT, GPR, ARIMA, ELM,SVM, LS-SVM)	Short-termWS forecasting	Improved forecast ACC, more probabilistic information.
Demolli et al. [116]	ML algorithms (LASSO, kNN, XGBoost, RF,SVR)	Long-term WP pre-diction	XGBoost, SVR, RF effective; RF best performer.
Xiao et al. [117]	Self-adaptive KELM	WP forecasting	Enhances training efficiency, re-duces retraining costs, improvesACC.
Cadenas et al. [118]	ARIMA, NARX	WS prediction	NARX shows less error com-pared to ARIMA.
Li et al. [119]	Improved Drag-onfly Algorithm-based SVM	Short-termWP forecasting	-
Tian et al. [120]	LMD, LSSVM, Firefly Algorithm	Short-termWS forecasting	-
Hong et al. [121]	CNN	Next-day WS pre-diction	-

V. Optimization Methods

Optimization plays a crucial role in the design, analysis, control, and operation of various real-world systems. It involves selecting the most suitable goals, variables, and constraints to devise scalable algorithms that can find optimal or nearly optimal solutions efficiently. The field of optimization has evolved significantly, especially with advancements in ML [122, 123]. In EM, nearly every article published in the last two decades underscores the urgent need for more efficient energy production and utilization. This has spurred research into complex optimization problems in ESs, employing approaches like ML-based optimization, real-time algorithms, heuristic, hyper-heuristic, and metaheuristic methods. EM optimization is crucial across various domains [124, 125, 126, 127]. Teng et al.'s research, for example, explored EM in electric vehicles and fuel cells to boost energy efficiency [128]. Perera et al. investigated the use of SL and TL in optimizing ESs. They proposed a HOA, named (SMANN-AEM), which merges Surrogate Models with ANN and AEM to expedite the optimization process while retaining ACC. The HOA was found to be about 17 times faster than the traditional AEM, and using SMTL with HOA could reduce computational time by up to 84%, making it feasible for regional or national ES optimization [129]. Ikeda et al. introduced a hybrid optimization method using Deep NN for day-to-day activity optimization in building energy and storage systems. The method, which predicts optimal performance of integrated cooling tower systems, could potentially reduce daily operating costs by over 13.4% [130]. Zhou et al. proposed a multivariate optimization method using ANN and an advanced algorithm for a hybrid system. Their findings suggested that the ANN-based learning algorithm outperforms traditional methods in ACC and computational efficiency for optimization tasks. Moreover, teaching-learning methods showed greater strength than other methods like Particle Swarm Optimization in optimizing overall energy production [131]. Ilbeigi et al. presented a model using MLP and GA to optimize energy consumption in an Iranian research center. The MLP model simulated the building's energy consumption, which was then optimized using GA, considering key variables. This optimization resulted in a significant reduction in energy consumption (about 35%) and demonstrated that the MLP model could accurately predict building energy consumption [132].

Naserbegi et al. explored the multi-objective optimization of a hybrid nuclear power plant using an ANN-GSA. The ANN, utilizing 10 thermodynamic inputs from the power plant, was employed to predict optimal performance for the optimization process. Their findings indicated the effectiveness of this approach for the given purpose [133]. Abbas et al. focused on optimizing the production capacity of RE systems with storage, employing an ANN-GA methodology. Their research demonstrated both high ACC and efficiency in computation time [71]. Similarly, Li et al. also applied the ANN-GA algorithm, but for optimizing engine efficiency, achieving results with suitable ACC and an acceptable computation period [134]. Xu et al. introduced a novel intelligent reasoning system for evaluating and optimizing energy consumption in industrial processes. This system comprised three methods were used for retrieving similar inputs. The system achieved an ACC of 91.7% and an optimization error below 13.5%, validated by experimental results. It also proved beneficial in reducing energy consumption, maintaining tool stability, and enhancing process efficiency [135]. Wen et al. utilized ANN for optimizing the design of wind turbine airfoils. By training data to predict the lift coefficient and the maximum lift-to-drag ratio of airfoils, their study presented new insights for airfoil optimization and significantly reduced the time required for optimization [136]. Monitoring and diagnosing faults in large-scale industrial processes and ESs is a critical challenge, with human errors accounting for approximately 70% of industrial accidents. Thus, developing efficient, reliable real-time DST for FDD is essential to enhance safety, environmental protection, and profitability [137]. The reliability, availability, and safety of equipment in ESs are paramount, necessitating effective monitoring and assessment tools [138, 139].

Faults in systems like wind turbines, which contain both mechanical and electrical components, require sophisticated detection technologies [140]. Effective fault analysis is crucial for minimizing disruptions and maintaining optimal performance in power systems [141]. The increasing use of AI and ML models aids in enhancing the speed and efficiency of these processes [142]. Yang et al. used in their work the SVR model for early-stage fault detection (FD) in wind turbines. They introduced penalty factors and slack variables in the SVR algorithm to improve its ability to filter unwanted signals and identify outliers, leading to better balance in false alarms and early FD [143]. Choi et al. utilized energy consumption forecasting to detect faults and abnormalities in tools. They applied a Random Forest algorithm to time series data, using outlier data detection when the model's ACC exceeded a certain threshold. The model proved effective for this purpose [144]. Wang et al. proposed an intelligent FD method for wind. This method demonstrated 100% detection ACC, proving its effectiveness in accurately identifying different states of rotary bearings [145]. Han et al. introduced a model using the Least Square SVM algorithm for FDD in chillers. This model outperformed Probabilistic NN and SVM in ACC, FD, and runtime, especially for system-level defects [146]. Helbing et al. reviewed Deep Learning-based methods for FD in wind turbines, examining most of the available methods [147]. Other studies using ML and DL for FDD include Wang et al.'s Hybrid Model with SVM- PSO for nuclear power plants [148]; Sarwar et al.'s use of the SVM algorithm for detecting high impedance faults in power distribution networks [149]; Eskandari et al.'s Ensemble Learning (EL) model for PV system FD [150]; Han et al.'s EL model for diagnosing building ES defects [151]; and Tightiz et al.'s application of the ANFIS model for diagnosing power transformer defects [152]. The Summary of ML and DL Techniques in Optimization and FDD in ESs is shown in Table 4.

Table 4: Summary of ML and DL Techniques in Optimization and FDD in ESs

Authors	**Model/Method Used**	**Application**	**Key Findings**
Teng et al.[128]	-	Energy Manage- ment in EVs and fuel cells	Boosting energy efficiency.
Perera et al. [129]	SL, TL, HOA (SMANN-AEM)	ES optimization	HOA significantly faster and more accurate.
Ikeda et al. [130]	Hybrid method with DNN	Building energy And storage sys-tems	Reduction in daily operating costs.
Zhou et al. [131]	ANN and advanced algorithms	Hybrid system op- timization	ANN-based algorithm outper- forms traditional methods.
Ilbeigi et al. [132]	MLP and GA	Energy consump- tion optimization	Significant reduction in energy consumption.
Naserbegi et al. [133]	ANN-based GSA	Optimization in hy- brid nuclear power plant	Effective in predicting optimal performance.
Abbasetal.	ANN-GA	RE system opti- mization	High ACC and efficiency in com- putation.
Lietal. [134]	ANN-GA	Engine efficiency optimization	Suitable ACC and acceptable computation period.
Xu et al. [135]	ICBR, ANFIS, VPSO	Industrial process energy optimiza- tion	High ACC and optimization er- ror below 13.5%.
Wen et al. [136]	ANN	Wind turbine airfoil design opti- mization	Insights for airfoil optimization, time-efficient.
Yang et al. [143]	SVR	FD in wind tur- bines	Improved early-stage FD.
Choi et al. [144]	Random Forest	FD in tools via en- ergy consumption forecasting	Effective for detecting outliers and abnormalities.
Wang et al. [145]	Beetle Antennae Search based SVM	FD in wind turbine bearings	100% detection ACC.
Han et al. [146]	Least Square SVM	FDD in chillers	Superior in ACC and runtime for system-level defects.
Zhao et al.	Review of AI-based methods	FD in building ESs	-
Helbing et al. [147]	Review of DL- based methods	FD in wind tur- bines	-
Wang et al. [148]	Hybrid Model with SVM-PSO	FDD in nuclear power plants	-

Sarwar et al. [149]	SVM algorithm	Detecting high impedance faults in power networks	-
Eskandari et al. [150]	EL (SVM, Naive Bayes, kNN)	PV system FD	-
Han et al. [151]	EL model	Diagnosing building ES defects	-
Tightiz et al. [152]	ANFIS model	Diagnosing power transformer defects	-

VI. Challenges of RE and the Role of Explainable AI

The integration of Renewable Energy (RE) sources into existing power systems, while crucial for a sustainable future, presents a myriad of challenges, prominently due to the intermittency and unpredictability of these energy sources. Solar and wind energies, heavily reliant on environmental conditions, lead to fluctuating energy production, posing significant hurdles in maintaining grid stability and reliability. While predictive models powered by Artificial Intelligence (AI) offer fore- casts for energy availability, their effectiveness is often hindered by the opaque nature of traditional AI models, which can undermine trust and understanding. Here, the application of Explainable Artificial Intelligence (XAI) emerges as a critical solution, enhancing transparency and reliability of these forecasts. XAI, by elucidating the decision-making processes of AI, mitigates the ambiguity surrounding predictive models, thereby fostering trust among grid operators and stakeholders. Furthermore, the complexity of merging RE sources with existing power grids requires sophisticated control and optimization strategies. AI models, though capable, often suffer from a ’black-box’ nature (figure 2), obscuring the understanding of decision-making processes. XAI ad- dresses this by shedding light on these processes, thereby assisting operators in comprehending and efficiently managing the integration of RE sources into the grid.

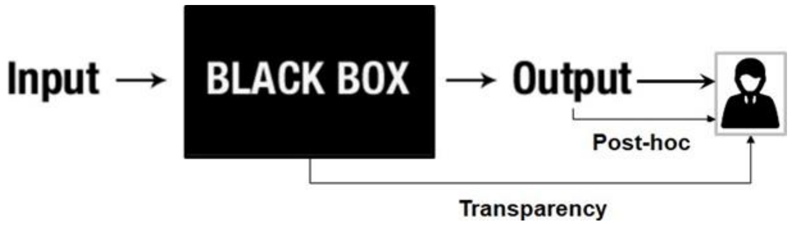

Fig. 2: transparency design and post-hoc explanation [153].

Another significant challenge is balancing the supply from renewable sources with fluctuating demand. AI models are instrumental in predicting demand patterns and adjusting the supply accordingly. However, for effective management, the rationale behind AI-based decisions must be transparent. XAI plays a vital role in this context by providing clear explanations of AI decisions, thereby ensuring better decision-making in real-time energy management. Maintenance and reliability are also key for optimal performance of RE systems. AI-driven pre- dictive maintenance can preempt equipment failures, but the complex algorithms used are often difficult to interpret. XAI becomes indispensable in such scenarios, offering clear and understand- able explanations for maintenance decisions, aiding in the formulation of efficient and effective maintenance schedules. Moreover, with constantly evolving energy policies and regulations, AI’s assistance in com- pliance monitoring becomes essential. Yet, decisions made by non-explainable AI could lead to regulatory challenges. XAI offers the transparency and accountability needed, ensuring that AI- driven solutions are in alignment with regulatory standards. Finally, public perception and acceptance are vital for the adoption of AI-driven solutions in RE. XAI can significantly contribute to enhancing public trust by demystifying AI decisions, mak- ing them more transparent and understandable. In conclusion, while RE sources offer numerous benefits, their integration is fraught with unique challenges that can be effectively mitigated with the aid of XAI. By rendering AI algorithms in the energy sector more transparent and understand- able, XAI not only bolsters operational efficiency but also builds trust among various stakeholders, facilitating a smoother and more acceptable transition to renewable energy sources [154-156].

VII. 7. CONCLUSION

In summary, this review has systematically examined the crucial intersection of RE systems and the rapidly evolving technologies of ML and DL. The urgency for adopting renewable sources such as solar and wind power is underscored by escalating energy demands, environmental challenges, and the imperative for sustainable energy practices. Our in-depth analysis highlights the substantial advancements that ML and DL technologies bring to the RE sector, enhancing efficiency, reliability, and predictability. Key areas where ML and DL exhibit their strengths include the prediction and optimization of energy consumption and production. These advanced technologies offer sophisticated tools for accurately forecasting energy demands and optimizing energy outputs, which are vital for effective energy management and maintaining grid stability. The application of ML and DL extends beyond forecasting to encompass optimization of operational parameters, maintenance schedules, and even in the early stages of planning and design of RE systems. However, our review also draws attention to the significant challenges associated with deploying AI technologies within the energy sector. Complexities in energy systems, the inherent variability of renewable sources, and the necessity for accurate and reliable predictions present considerable hurdles. Additionally, the integration of these technologies into existing energy grids necessitates a careful balance of technical, economic, and regulatory considerations. The role of Explainable AI (XAI) emerges as a critical component in this landscape. As AI models increase in complexity, ensuring their transparency and understandability becomes paramount for building trust and encouraging broader adoption. XAI represents a crucial bridge between cutting-edge AI models and their practical, user-friendly application within the energy sector.

Conclusively, the integration of ML and DL into RE systems heralds a promising path to- ward a sustainable and efficient energy future. While the journey is fraught with challenges, the continued research and innovation in this field are vital. It is crucial that future endeavors not only concentrate on technological advancements but also prioritize making these technologies accessible, comprehensible, and aligned with overarching sustainability objectives. The potential of ML and DL in revolutionizing the RE sector is immense, but its realization hinges on a balanced approach that addresses technological capabilities alongside ethical, societal, and environmental considerations.

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CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

REFERENCES

[1] L. Cameron and B. Van Der Zwaan. Employment factors for wind and solar energy technologies: A literature review. Renewable and Sustainable Energy Reviews, 45:160–172, 2015.

[2] A. Eid, S. Kamel, and L. Abualigah. Marine predators algorithm for optimal allocation of active and reactive power resources in distribution networks. Neural Computing and Applications, 33:14327–14355, 2021.

[3] B. Van der Zwaan, L. Cameron, and T. Kober. Potential for renewable energy jobs in the middle east. Energy Policy, 60:296–304, 2013.

[4] K. Connolly. The regional economic impacts of offshore wind energy developments in scot- land. Renewable Energy, 160:148–159, 2020.

[5] G. Alkawsi, Y. Baashar, A.A. Alkahtani, C.W. Lim, S.K. Tiong, and M. Khudari. Viability assessment of small-scale on-grid wind energy generator for households in malaysia. Energies, 14:3391, 2021.

[6] M.H. Hassan, S. Kamel, L. Abualigah, and A. Eid. Development and application of slime mould algorithm for optimal economic emission dispatch. Expert Systems with Applications, 182:115205, 2021.

[7] S. Wang, H. Jia, L. Abualigah, Q. Liu, and R. Zheng. An improved hybrid Aquila optimizer and harris hawks algorithm for solving industrial engineering optimization problems. Processes, 9:1551, 2021.

[8] A. Ziadeh, L. Abualigah, M.A. Elaziz, C.B. Şahin, A.A. Almazroi, and M. Omari. Augmented grasshopper optimization algorithm by differential evolution: A power scheduling application in smart homes. Multimedia Tools and Applications, 80:31569–31597, 2021.

[9] R. Vatti, N. Vatti, K. Mahender, P.L. Vatti, and B. Krishnaveni. Solar energy harvesting for smart farming using nanomaterial and machine learning. In IOP Conference Series: Materials Science and Engineering, volume 981, page 032009. Chennai, India, 2020.

[10] H. Liu, C. Chen, X. Lv, X. Wu, and M. Liu. Deterministic wind energy forecasting: A review of intelligent predictors and auxiliary methods. Energy Conversion and Management, 195:328–345, 2019.

[11] R. Spée, S. Bhowmik, and J.H. Enslin. Novel control strategies for variable-speed doubly fed wind power generation systems. Renewable Energy, 6:907–915, 1995.

[12] L. Abualigah, A. Diabat, P. Sumari, and A.H. Gandomi. Applications, deployments, and integration of internet of drones (iod): A review. IEEE Sensors Journal, 21:25532–25546, 2021.

[13] M. Abd Elaziz, L. Abualigah, R.A. Ibrahim, and I. Attiya. Iot workflow scheduling using intelligent arithmetic optimization algorithm in fog computing. Computational Intelligence and Neuroscience, page 9114113, 2021.

[14] S. Canbulat, K. Balci, O. Canbulat, and I.S. Bayram. Techno-economic analysis of on-site energy storage units to mitigate wind energy curtailment: A case study in scotland. Energies, 14:1691, 2021.

[15] M. Joos and I. Staffell. Short-term integration costs of variable renewable energy: Wind curtailment and balancing in Britain and Germany. Renewable and Sustainable Energy Reviews, 86:45–65, 2018.

[16] E. Ela, B. Kirby, N. Navid, and J.C. Smith. Effective ancillary services market designs on high wind power penetration systems. In 2012 IEEE Power and Energy Society General Meeting, pages 1–8. San Diego, CA, USA, 2012.

[17] W. Qi, J. Liu, X. Chen, and P.D. Christofides. Supervisory predictive control of standalone wind/solar energy generation systems. IEEE Transactions on Control Systems Technology, 19:199–207, 2010.

[18] M. Jamei, M. Karbasi, M. Mosharaf-Dehkordi, I.A. Olumegbon, L. Abualigah, Z. Said, and
A. Asadi. Estimating the density of hybrid nanofluids for thermal energy application: Appli- cation of non-parametric and evolutionary polynomial regression data-intelligent techniques. Measurement, page 110524, 2021.

[19] M.H. Nadimi-Shahraki, A. Fatahi, H. Zamani, S. Mirjalili, and L. Abualigah. An improved moth-flame optimization algorithm with adaptation mechanism to solve numerical and me- chanical engineering problems. Entropy, 23:1637, 2021.

[20] R.A. Zitar, L. Abualigah, and N.A. Al-Dmour. Review and analysis for the red deer algorithm. Journal of Ambient Intelligence and Humanized Computing, pages 1–11, 2021.

[21] L. Abualigah, A. Diabat, and M.A. Elaziz. Improved slime mould algorithm by opposition- based learning and levy flight distribution for global optimization and advances in real-world engineering problems. Journal of Ambient Intelligence and Humanized Computing, pages 1–40, 2021.

[22] R. Zheng, H. Jia, L. Abualigah, Q. Liu, and S. Wang. Deep ensemble of slime mold algorithm and arithmetic optimization algorithm for global optimization. Processes, 9:1774, 2021.

[23] S.K. Nandi, M.N. Hoque, H.R. Ghosh, and R. Chowdhury. Assessment of wind and solar energy resources in Bangladesh. Arabian Journal of Science and Engineering, 38:3113–3123, 2013.

[24] C. Schillings, R. Meyer, and F. Trieb. Final report of solar and wind energy resource assessment (swera), 2004.

[25] D. Yousri, M. Abd Elaziz, D. Oliva, L. Abualigah, M.A. Al-qaness, and A.A. Ewees. Reli- able applied objective for identifying simple and detailed photovoltaic models using modern metaheuristics: Comparative study. Energy Conversion and Management, 223:113279, 2020.

[26] N.M. Nasab, J. Kilby, and L. Bakhtiaryfard. Case study of a hybrid wind and tidal turbines system with a micro grid for power supply to a remote off-grid community in new zealand. Energies, 14:3636, 2021.

[27] S. Mohanty, P.K. Patra, S.S. Sahoo, and A. Mohanty. Forecasting of solar energy with application for a growing economy like India: Survey and implication. Renewable and Sustainable Energy Reviews, 78:539–553, 2017.

[28] J. Jurasz, J. Mikulik, P.B. Dąbek, M. Guezgouz, and B. Kaźmierczak. Complementarity and 'resource droughts' of solar and wind energy in Poland: An era5-based analysis. Energies, 14:1118, 2021.

[29] Zeren Jiao et al. Machine learning and deep learning in chemical health and safety: a systematic review of techniques and applications. ACS Chemical Health & Safety, 27(6):316– 334, 2020.

[30] Wojciech Samek et al. Explaining deep neural networks and beyond: A review of methods and applications. Proceedings of the IEEE, 109(3):247–278, 2021.

[31] Summaira Jabeen et al. A review on methods and applications in multimodal deep learning. ACM Transactions on Multimedia Computing, Communications and Applications, 19(2s):1– 41, 2023.

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

[33] Adrian BR Shatte, Delyse M Hutchinson, and Samantha J Teague. Machine learning in men- tal health: a scoping review of methods and applications. Psychological Medicine, 49(9):1426– 1448, 2019.

[34] Mahyar Amini and Ali Rahmani. How strategic agility affects the competitive capabilities of private banks. International Journal of Basic and Applied Sciences, 10(01):8397–8406, 2023.

[35] Adrian Carrio et al. A review of deep learning methods and applications for unmanned aerial vehicles. Journal of Sensors, 2017.

[36] Mahyar Amini and Ali Rahmani. Achieving financial success by pursuing environmental and social goals: A comprehensive literature review and research agenda for sustainable investment. World Information Technology and Engineering Journal, 10(04):1286–1293, 2023.

[37] Teng Zhou, Zhen Song, and Kai Sundmacher. Big data creates new opportunities for materials research: a review on methods and applications of machine learning for materials design. Engineering, 5(6):1017–1026, 2019.

[38] Mahyar Amini and Zavareh Bozorgasl. A game theory method to cyber-threat information sharing in cloud computing technology. International Journal of Computer Science and Engineering Research, 11(4):549–560, 2023.

[39] Li Deng and Dong Yu. Deep learning: methods and applications. Foundations and Trends® in Signal Processing, 7(3-4):197–387, 2014.

[40] Somayeh Nazari Enjedani and Mahyar Amini. The role of traffic impact effect on transportation planning and sustainable traffic management in metropolitan regions. International Journal of Smart City Planning Research, 12(2023):688–700, 2023.

[41] Junyi Chai et al. Deep learning in computer vision: A critical review of emerging techniques and application scenarios. Machine Learning with Applications, 6:100134, 2021.

[42] Negar Jahanbakhsh Javidi and Mahyar Amini. Evaluating the effect of supply chain management practice on implementation of halal agroindustry and competitive advantage for small and medium enterprises. International Journal of Computer Science and Information Technology, 15(6):8997–9008, 2023.

[43] Samira Pouyanfar et al. A survey on deep learning: Algorithms, techniques, and applications. ACM Computing Surveys (CSUR), 51(5):1–36, 2018.

[44] Mahyar Amini and Negar Jahanbakhsh Javidi. A multi-perspective framework established on diffusion of innovation (doi) theory and technology, organization and environment (toe) framework toward supply chain management system based on cloud computing technology for small and medium enterprises. International Journal of Information Technology and Innovation Adoption, 11(8):1217–1234, 2023.

[45] Jie Zhou et al. Graph neural networks: A review of methods and applications. AI Open, 1:57–81, 2020.

[46] Mahyar Amini and Ali Rahmani. Agricultural databases evaluation with machine learning procedure. Australian Journal of Engineering and Applied Science, 8(6):39–50, 2023.

[47] Jinjiang Wang et al. Deep learning for smart manufacturing: Methods and applications. Journal of Manufacturing Systems, 48:144–156, 2018.

[48] Mahyar Amini and Ali Rahmani. Machine learning process evaluating damage classification of composites. International Journal of Science and Advanced Technology, 9(12):240–250, 2023.

[49] Shanaka Kristombu Baduge et al. Artificial intelligence and smart vision for building and construction 4.0: Machine and deep learning methods and applications. Automation in Construction, 141:104440, 2022.

[50] Mahyar Amini, Koosha Sharifani, and Ali Rahmani. Machine learning model towards evaluating data gathering methods in manufacturing and mechanical engineering. International Journal of Applied Science and Engineering Research, 15(4):349–362, 2023.

[51] Mohamed Abd Elaziz et al. Advanced metaheuristic optimization techniques in applications of deep neural networks: a review. Neural Computing and Applications, pages 1–21, 2021.

[52] Koosha Sharifani, Mahyar Amini, Yaser Akbari, and Javad Aghajanzadeh Godarzi. Operating machine learning across natural language processing techniques for improvement of fabricated news model. International Journal of Science and Information System Research, 12(9):20–44, 2022.

[53] Ebrahim Balouji et al. A lstm-based deep learning method with application to voltage dip classification. In 2018 18th International Conference on Harmonics and Quality of Power (ICHQP). IEEE, 2018.

[54] Mahyar Amini et al. Mahamgostar.com as a case study for adoption of laravel framework as the best programming tools for php based web development for small and medium enterprises. Journal of Innovation & Knowledge, pages 100–110, 2021.

[55] William L Hamilton, Rex Ying, and Jure Leskovec. Representation learning on graphs: Methods and applications. arXiv preprint arXiv:1709.05584, 2017.

[56] Mahyar Amini and Aryati Bakri. Cloud computing adoption by smes in the Malaysia: A multiperspective framework based on doi theory and toe framework. Journal of Information Technology & Information Systems Research (JITISR), 9(2):121–135, 2015.

[57] Mahyar Amini and Nazli Sadat Safavi. A dynamic sla aware heuristic solution for iaas cloud placement problem without migration. International Journal of Computer Science and Information Technologies, 6(11):25–30, 2014.

[58] Christian Janiesch, Patrick Zschech, and Kai Heinrich. Machine learning and deep learning. Electronic Markets, 31(3):685–695, 2021.

[59] Mahyar Amini. The factors that influence on adoption of cloud computing for small and medium enterprises, 2014.

[60] Neha Sharma, Reecha Sharma, and Neeru Jindal. Machine learning and deep learning applications-a vision. Global Transitions Proceedings, 2(1):24–28, 2021.

[61] Mahyar Amini et al. Development of an instrument for assessing the impact of environmental context on adoption of cloud computing for small and medium enterprises. Australian Journal of Basic and Applied Sciences (AJBAS), 8(10):129–135, 2014.

[62] Mehul Mahrishi et al., editors. Machine Learning and Deep Learning in Real-Time Applications. IGI Global, 2020.

[63] Mahyar Amini et al. The role of top manager behaviors on adoption of cloud computing for small and medium enterprises. Australian Journal of Basic and Applied Sciences (AJBAS), 8(1):490–498, 2014.

[64] Amitha Mathew, P Amudha, and S Sivakumari. Deep learning techniques: an overview. In Advanced Machine Learning Technologies and Applications: Proceedings of AMLTA 2020, pages 599–608, 2021.

[65] Mahyar Amini and Nazli Sadat Safavi. A dynamic sla aware solution for iaas cloud placement problem using simulated annealing. International Journal of Computer Science and Information Technologies, 6(11):52–57, 2014.

[66] Li Deng and Dong Yu. Foundations and Trends in Signal Processing: DEEP LEARN- ING–Methods and Applications. 2014.

[67] Nazli Sadat Safavi, Nor Hidayati Zakaria, and Mahyar Amini. The risk analysis of system selection and business process re-engineering towards the success of enterprise resource plan- ning project for small and medium enterprise. World Applied Sciences Journal (WASJ), 31(9):1669–1676, 2014.

[68] Kaushik Dushyant et al. Utilizing machine learning and deep learning in cybersecurity: An innovative approach. In Cyber Security and Digital Forensics, pages 271–293, 2022.

[69] Nazli Sadat Safavi, Mahyar Amini, and Seyyed AmirAli Javadinia. The determinant of adoption of enterprise resource planning for small and medium enterprises in iran. International Journal of Advanced Research in IT and Engineering (IJARIE), 3(1):1–8, 2014.

[70] Yang Xin et al. Machine learning and deep learning methods for cybersecurity. IEEE Access, 6:35365–35381, 2018.

[71] Nazli Sadat Safavi et al. An effective model for evaluating organizational risk and cost in erp implementation by sme. IOSR Journal of Business and Management (IOSR-JBM), 10(6):70–75, 2013.

[72] Shaveta Dargan et al. A survey of deep learning and its applications: a new paradigm to machine learning. Archives of Computational Methods in Engineering, 27:1071–1092, 2020.

[73] Nazli Sadat Safavi et al. An effective model for evaluating organizational risk and cost in erp implementation by sme. IOSR Journal of Business and Management (IOSR-JBM), 10(6):61–66, 2013.

[74] Isabella Castiglioni et al. Ai applications to medical images: From machine learning to deep learning. Physica Medica, 83:9–24, 2021.

[75] Mahyar Amini and Nazli Sadat Safavi. Critical success factors for erp implementation. International Journal of Information Technology & Information Systems, 5(15):1–23, 2013.

[76] G.Y. Yun, H.J. Kong, H. Kim, and J.T. Kim. A field survey of visual comfort and lighting energy consumption in open plan offices. Energy and Buildings, 46:146–151, 2012.

[77] Z. Xuan, Z. Xuehui, L. Liequan, F. Zubing, Y. Junwei, and P. Dongmei. Forecasting performance comparison of two hybrid machine learning models for cooling load of a large-scale commercial building. Journal of Building Engineering, 21:64–73, 2019.

[78] J. Runge, R. Zmeureanu, and M. le Cam. Hybrid short-term forecasting of the electric demand of supply fans using machine learning. Journal of Building Engineering, 29:101144, 2020.

[79] A. Ghodrati, R. Zahedi, and A. Ahmadi. Analysis of cold thermal energy storage using phase change materials in freezers. Journal of Energy Storage, 51:104433, 2022.

[80] C. Fan, F. Xiao, and S. Wang. Development of prediction models for next-day building energy consumption and peak power demand using data mining techniques. Applied Energy, 127:1–10, 2014.

[81] K. Bot, A. Ruano, and M. Ruano. Forecasting electricity demand in households using moga- designed artificial neural networks. IFAC Papers On Line, 53:8225–8230, 2020.

[82] H. Bian, Y. Zhong, J. Sun, and F. Shi. Study on power consumption load forecast based on k-means clustering and fcm–bp model. Energy Reports, 6:693–700, 2020.

[83] K. Amasyali and N.M. El-Gohary. A review of data-driven building energy consumption prediction studies. Renewable and Sustainable Energy Reviews, 81:1192–1205, 2018.

[84] C. Deb, F. Zhang, J. Yang, S.E. Lee, and K.W. Shah. A review on time series forecasting techniques for building energy consumption. Renewable and Sustainable Energy Reviews, 74:902–924, 2017.

[85] S. Walker, W. Khan, K. Katic, W. Maassen, and W. Zeiler. Accuracy of different machine learning algorithms and added-value of predicting aggregated-level energy performance of commercial buildings. Energy and Buildings, 209:109705, 2020.

[86] A.I. Grimaldo and J. Novak. Combining machine learning with visual analytics for explainable forecasting of energy demand in prosumer scenarios. Procedia Computer Science, 175:525–532, 2020.

[87] Y. Liu, H. Chen, L. Zhang, X. Wu, and X.-j. Wang. Energy consumption prediction and diagnosis of public buildings based on support vector machine learning: A case study in china. Journal of Cleaner Production, 272:122542, 2020.

[88] F. Kaytez. A hybrid approach based on autoregressive integrated moving average and least- square support vector machine for long-term forecasting of net electricity consumption. Energy, 197:117200, 2020.

[89] G.-F. Fan, X. Wei, Y.-T. Li, and W.-C. Hong. Forecasting electricity consumption using a novel hybrid model. Sustainable Cities and Society, 61:102320, 2020.

[90] R. Jamil. Hydroelectricity consumption forecast for Pakistan using arima modeling and supply-demand analysis for the year 2030. Renewable Energy, 154:1–10, 2020.

[91] O.F. Beyca, B.C. Ervural, E. Tatoglu, P.G. Ozuyar, and S. Zaim. Using machine learning tools for forecasting natural gas consumption in the province of istanbul. Energy Economics, 80:937–949, 2019.

[92] L. Wen, K. Zhou, and S. Yang. Load demand forecasting of residential buildings using a deep learning model. Electric Power Systems Research, 179:106073, 2020.

[93] E.U. Haq, X. Lyu, Y. Jia, M. Hua, and F. Ahmad. Forecasting household electric appliances consumption and peak demand based on hybrid machine learning approach. Energy Reports, 6:1099–1105, 2020.

[94] G. Hafeez, K.S. Alimgeer, and I. Khan. Electric load forecasting based on deep learning and optimized by heuristic algorithm in smart grid. Applied Energy, 269:114915, 2020.

[95] A. Khan, H. Chiroma, M. Imran, J.I. Bangash, M. Asim, M.F. Hamza, and H. Aljuaid. Forecasting electricity consumption based on machine learning to improve performance: A case study for the organization of petroleum exporting countries (opec). Computers and Electrical Engineering, 86:106737, 2020.

[96] M.-R. Kazemzadeh, A. Amjadian, and T. Amraee. A hybrid data mining driven algorithm for long term electric peak load and energy demand forecasting. Energy, 204:117948, 2020.

[97] S. Fathi, R. Srinivasan, A. Fenner, and S. Fathi. Machine learning applications in urban building energy performance forecasting: A systematic review. Renewable and Sustainable Energy Reviews, 133:110287, 2020.

[98] S.F. Moosavian, R. Zahedi, and A. Hajinezhad. Economic, environmental and social impact of carbon tax for iran: A computable general equilibrium analysis. Energy Science and Engineering, 10:13–29, 2022.

[99] G. Narvaez, L.F. Giraldo, M. Bressan, and A. Pantoja. Machine learning for site-adaptation and solar radiation forecasting. Renewable Energy, 167:333–342, 2021.

[100] Y. Feng, D. Gong, Q. Zhang, S. Jiang, L. Zhao, and N. Cui. Evaluation of temperature-based machine learning and empirical models for predicting daily global solar radiation. Energy Conversion and Management, 198:111780, 2019.

[101] J. Fan, L. Wu, F. Zhang, H. Cai, W. Zeng, X. Wang, and H. Zou. Empirical and machine learning models for predicting daily global solar radiation from sunshine duration: A review and case study in china. Renewable and Sustainable Energy Reviews, 100:186–212, 2019.

[102] H. Sharadga, S. Hajimirza, and R.S. Balog. Time series forecasting of solar power generation for large-scale photovoltaic plants. Renewable Energy, 150:797–807, 2020.

[103] C. Voyant, G. Notton, S. Kalogirou, M.-L. Nivet, C. Paoli, F. Motte, and A. Fouilloy. Machine learning methods for solar radiation forecasting: A review. Renewable Energy, 105:569–582, 2017.

[104] J. Huertas-Tato, R. Aler, I.M. Galván, F.J. Rodríguez-Benítez, C. Arbizu-Barrena, and D. Pozo-Vázquez. A short-term solar radiation forecasting system for the iberian peninsula. part 2: Model blending approaches based on machine learning. Solar Energy, 195:685–696, 2020.

[105] T.R. Govindasamy and N. Chetty. Machine learning models to quantify the influence of pm10 aerosol concentration on global solar radiation prediction in south africa. Clean Engineering and Technology, 2:100042, 2021.

[106] A.E. Gürel, Ü. Ağbulut, and Y. Biçen. Assessment of machine learning, time series, response surface methodology and empirical models in prediction of global solar radiation. Journal of Cleaner Production, 277:122353, 2020.

[107] M. Alizamir, S. Kim, O. Kisi, and M. Zounemat-Kermani. A comparative study of several machine learning based non-linear regression methods in estimating solar radiation: Case studies of the usa and turkey regions. Energy, 197:117239, 2020.

[108] R. Srivastava, A. Tiwari, and V. Giri. Solar radiation forecasting using mars, cart, m5, and random forest model: A case study for India. Heliyon, 5:e02692, 2019.

[109] L. Benali, G. Notton, A. Fouilloy, C. Voyant, and R. Dizene. Solar radiation forecasting using artificial neural network and random forest methods: Application to normal beam, horizontal diffuse and global components. Renewable Energy, 132:871–884, 2019.

[110] A. Khosravi, R.N.N. Koury, L. Machado, and J.J.G. Pabon. Prediction of hourly solar radiation in abu musa island using machine learning algorithms. Journal of Cleaner Production, 176:63–75, 2018.

[111] C. Li, S. Lin, F. Xu, D. Liu, and J. Liu. Short-term wind power prediction based on data mining technology and improved support vector machine method: A case study in northwest china. Journal of Cleaner Production, 205:909–922, 2018.

[112] W. Yang, J. Wang, H. Lu, T. Niu, and P. Du. Hybrid wind energy forecasting and analysis system based on divide and conquer scheme: A case study in china. Journal of Cleaner Production, 222:942–959, 2019.

[113] Z. Lin and X. Liu. Wind power forecasting of an offshore wind turbine based on high- frequency scada data and deep learning neural network. Energy, 201:117693, 2020.

[114] A. Zendehboudi, M. Baseer, and R. Saidur. Application of support vector machine models for forecasting solar and wind energy resources: A review. Journal of Cleaner Production, 199:272–285, 2018.

[115] J. Wang and J. Hu. A robust combination approach for short-term wind speed forecasting and analysis–combination of the arima (autoregressive integrated moving average), elm (extreme learning machine), svm (support vector machine) and lssvm (least square svm) forecasts using a gpr (gaussian process regression) model. Energy, 93:41–56, 2015.

[116] H. Demolli, A.S. Dokuz, A. Ecemis, and M. Gokcek. Wind power forecasting based on daily wind speed data using machine learning algorithms. Energy Conversion and Management, 198:111823, 2019.

[117] L. Xiao, W. Shao, F. Jin, and Z. Wu. A self-adaptive kernel extreme learning machine for short-term wind speed forecasting. Applied Soft Computing, 99:106917, 2021.

[118] E. Cadenas, W. Rivera, R. Campos-Amezcua, and C. Heard. Wind speed prediction using a univariate arima model and a multivariate narx model. Energies, 9:109, 2016.

[119] L.-L. Li, X. Zhao, M.-L. Tseng, and R.R. Tan. Short-term wind power forecasting based on support vector machine with improved dragonfly algorithm. Journal of Cleaner Production, 242:118447, 2020.

[120] Z. Tian. Short-term wind speed prediction based on lmd and improved fa optimized combined kernel function lssvm. Engineering Applications of Artificial Intelligence, 91:103573, 2020.

[121] Y.-Y. Hong and T.R.A. Satriani. Day-ahead spatiotemporal wind speed forecasting using robust design-based deep learning neural network. Energy, 209:118441, 2020.

[122] R. Zahedi, A. Ahmadi, R. Eskandarpanah, and M. Akbari. Evaluation of resources and potential measurement of wind energy to determine the spatial priorities for the construction of wind-driven power plants in damghan city. International Journal of Sustainable Energy and Environmental Research, 11:1–22, 2022.

[123] R.Y. Zhang, C. Josz, and S. Sojoudi. Conic optimization for control, energy systems, and machine learning: Applications and algorithms. Annual Review of Control, 47:323–340, 2019.

[124] D.A. Narciso and F. Martins. Application of machine learning tools for energy efficiency in industry: A review. Energy Reports, 6:1181–1199, 2020.

[125] A.S. Azad, M.S.A. Rahaman, J. Watada, P. Vasant, and J.A.G. Vintaned. Optimization of the hydropower energy generation using meta-heuristic approaches: A review. Energy Reports, 6:2230–2248, 2020.

[126] S. Acarer, Ç. Uyulan, and Z.H. Karadeniz. Optimization of radial inflow wind turbines for urban wind energy harvesting. Energy, 202:117772, 2020.

[127] S. Salimi and A. Hammad. Optimizing energy consumption and occupants comfort in open- plan offices using local control based on occupancy dynamic data. Building and Environment, 176:106818, 2020.

[128] T. Teng, X. Zhang, H. Dong, and Q. Xue. A comprehensive review of energy management optimization strategies for fuel cell passenger vehicle. International Journal of Hydrogen Energy, 45:20293–20303, 2020.

[129] A.T.D. Perera, P.U. Wickramasinghe, V.M. Nik, and J.-L. Scartezzini. Machine learning methods to assist energy system optimization. Applied Energy, 243:191–205, 2019.

[130] S. Ikeda and T. Nagai. A novel optimization method combining metaheuristics and machine learning for daily optimal operations in building energy and storage systems. Applied Energy, 289:116716, 2021.

[131] Y. Zhou, S. Zheng, and G. Zhang. Artificial neural network based multivariable optimization of a hybrid system integrated with phase change materials, active cooling and hybrid ventilations. Energy Conversion and Management, 197:111859, 2019.

[132] M. Ilbeigi, M. Ghomeishi, and A. Dehghanbanadaki. Prediction and optimization of energy consumption in an office building using artificial neural network and a genetic algorithm. Sustainable Cities and Society, 61:102325, 2020.

[133] A. Naserbegi and M. Aghaie. Multi-objective optimization of hybrid nuclear power plant cou- pled with multiple effect distillation using gravitational search algorithm based on artificial neural network. Thermal Science and Engineering Progress, 19:100645, 2020.

[134] F. Abbas, S. Habib, D. Feng, and Z. Yan. Optimizing generation capacities incorporating renewable energy with storage systems using genetic algorithms. Electronics, 7:100, 2018.

[135] L. Xu, C. Huang, C. Li, J. Wang, H. Liu, and X. Wang. A novel intelligent reasoning system to estimate energy consumption and optimize cutting parameters toward sustainable machining. Journal of Cleaner Production, 261:121160, 2020.

[136] H. Wen, S. Sang, C. Qiu, X. Du, X. Zhu, and Q. Shi. A new optimization method of wind turbine airfoil performance based on bessel equation and gabp artificial neural network. Energy, 187:116106, 2019.

[137] M. El Koujok, A. Ragab, and M. Amazouz. A multi-agent approach based on machine- learning for fault diagnosis. IFAC PapersOnLine, 52:103–108, 2019.

[138] A. Deleplace, V. Atamuradov, A. Allali, J. Pellé, R. Plana, and G. Alleaume. Ensemble learning-based fault detection in nuclear power plant screen cleaners. IFAC PapersOnLine, 53:10354–10359, 2020.

[139] W. Zhang, X. Li, H. Ma, Z. Luo, and X. Li. Federated learning for machinery fault diagnosis with dynamic validation and self-supervision. Knowledge-Based Systems, 213:106679, 2021.

[140] Y. Pang, L. Jia, X. Zhang, Z. Liu, and D. Li. Design and implementation of automatic fault diagnosis system for wind turbine. Computers and Electrical Engineering, 87:106754, 2020.

[141] R. Zahedi, A. Ahmadi, and R. Dashti. Energy, exergy, exergoeconomic and exergoenviron- mental analysis and optimization of quadruple combined solar, biogas, src and orc cycles with methane system. Renewable and Sustainable Energy Reviews, 150:111420, 2021.

[142] A.E.L. Rivas and T. Abrão. Faults in smart grid systems: Monitoring, detection and classification. Electric Power Systems Research, 189:106602, 2020.

[143] C. Yang, J. Liu, Y. Zeng, and G. Xie. Real-time condition monitoring and fault detection of components based on machine-learning reconstruction model. Renewable Energy, 133:433– 441, 2019.

[144] W.H. Choi, J. Kim, and J.Y. Lee. Development of fault diagnosis models based on predicting energy consumption of a machine tool spindle. Procedia Manufacturing, 51:353–358, 2020.

[145] Z. Wang, L. Yao, Y. Cai, and J. Zhang. Mahalanobis semi-supervised mapping and beetle antennae search based support vector machine for wind turbine rolling bearings fault diagnosis. Renewable Energy, 155:1312–1327, 2020.

[146] H. Han, X. Cui, Y. Fan, and H. Qing. Least squares support vector machine (ls-svm)-based chiller fault diagnosis using fault indicative features. Applied Thermal Engineering, 154:540– 547, 2019.

[147] G. Helbing and M. Ritter. Deep learning for fault detection in wind turbines. Renewable and Sustainable Energy Reviews, 98:189–198, 2018.

[148] H. Wang, M.-J. Peng, J.W. Hines, G.-y. Zheng, Y.-K. Liu, and B.R. Upadhyaya. A hy- brid fault diagnosis methodology with support vector machine and improved particle swarm optimization for nuclear power plants. ISA Transactions, 95:358–371, 2019.

[149] M. Sarwar, F. Mehmood, M. Abid, A.Q. Khan, S.T. Gul, and A.S. Khan. High impedance fault detection and isolation in power distribution networks using support vector machines. Journal of King Saud University - Engineering Sciences, 32:524–535, 2019.

[150] A. Eskandari, J. Milimonfared, and M. Aghaei. Line-line fault detection and classification for photovoltaic systems using ensemble learning model based on iv characteristics. Solar Energy, 211:354–365, 2020.

[151] H. Han, Z. Zhang, X. Cui, and Q. Meng. Ensemble learning with member optimization for fault diagnosis of a building energy system. Energy and Buildings, 226:110351, 2020.

[152] L. Tightiz, M.A. Nasab, H. Yang, and A. Addeh. An intelligent system based on optimized anfis and association rules for power transformer fault diagnosis. ISA Transactions, 103:63– 74, 2020.

[153] Feiyu Xu, Hans Uszkoreit, Yangzhou Du, Wei Fan, Dongyan Zhao, and Jun Zhu. Explainable AI: A Brief Survey on History, Research Areas, Approaches and Challenges, pages 563–574. 09 2019.

[154] Hameed G. Juma'a and Thamir H. Atyia: DESIGN A 91-MULTILEVEL INVERTER CIRCUIT USING SOLAR PV SYSTEM SOURCES, PRZEGLĄD ELEKTROTECHNICZNY 2023-11, 2023, nr katalogowy: 146208, DOI:10.15199/48.2023.11.22.

[155] Mohib A. Qasim, Thamir H. Atyia: Design and Implementation of VSI for Solar Water Pump Control, Tikrit Journal of Engineering Science, Vol. 31 No. 1 (2024): Vol.31, No.1, 2024, DOI: https://doi.org/10.25130/tjes.31.1.17.

[156] Kutaiba K. Khaleel; Ahmed M. T. Ibraheem Al-Naib; Thamir H. Atyia: An efficient wireless monitoring system for photovoltaic panels using bluetooth technology, AIP Conf. Proc. 2885, 020001 (2024) https://doi.org/10.1063/5.0182370.