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Literature review on AI for energy forecasting

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***Abstract*— Energy management is a current topic due to the rising of costs, and climate change. This paper aims to study Artificial Intelligence (AI) to make energy consumption predictions. A deep literature review was carried out using Scopus database, clustering papers on short- and long-term forecast. Moreover, sustainability is a major concern and energy forecasting in both short and long periods can be successfully made with Machine Learning, Neural Network, Deep Learning, and Grey models. Therefore, AI models improve energy consumption forecast and energy allocation, reducing cost and carbon emissions.**

Keywords— Energy, Artificial Intelligence, AI, Machine Learning, Deep Learning, Forecasting, Sustainability, Literature Review

I. INTRODUCTION

In recent years, electrical energy demand exploded [1] and the concept of renewable energy and environmental sustainability has received growing attention from governments and businesses, due to the current disruption of environment [2], [3], [4], [5], [6]. To date, the energy sector is considered a fundamental pillar of the country's economy, playing a crucial role in supporting development, competitiveness, and quality of life. Its importance is reflected in various spheres of the economy, including manufacturing industries, services, and transportation. The continuity and quality of energy supply have become essential to ensure the stability and sustainability of the country's socioeconomic development [7], [8], [9], [10]. The transition to more sustainable energy sources, with the reduction of GHG [11], [12], has emerged as a strategic priority, in line with the "Paris Agreement" (an international treaty on climate change) signed on December 12, 2015, which outlines a path for the decarbonization of the economy, with the goal of limiting global warming to well below 2 degrees Celsius. China energy production is still based per 90% on fossil fuels [13], of which 50% based on coal [8], and aims to reach carbon neutrality by 2060 [8]. Due to this great interest for energy savings and reducing human footprint over environment, utilizing Industry 4.0 technologies becomes a pillar towards sustainability [14]. In particular, AI can provide great insight into stochastic systems [15], [16] like energy consumption and thus help decision-makers to base their moves on reliable predictions [17], improving the entire Supply Chain [14]. To provide value in this direction, this paper aims to carry out a detailed analysis of the existing literature to better understand the correlations between AI and energy forecasting. In particular, models for short and long periods predictions have been considered.

II. PROBLEM STATEMENT AND RQS

Energy management is a main concern worldwide. Industry 4.0 can provide new technologies useful to deal with energy consumption and savings. In particular, AI can be used for forecasting the usage and production. However, as this is a very new topic, a literature review is required to provide insight in the current trends and existing studied. The problem has been then translated into 2 research questions (RQs) to better face it. *1)"How can AI provide benefits in energy prediction?".* This general question was set to look for general information about AI in energy forecasting. *2) "Does short and long period require different models for forecasting?".* This 2nd question is more specific and aims to understand if there are model more performing on short or long period.

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III. METHODOLOGY

The research has been carried out using Scopus database to identify scientific articles related to the chosen topic. To perform the best possible analysis, these keywords were initially selected based on the titles, abstracts, and keywords of the articles. The results are shown in Table I. At first there were 20.389 records. Since this number was too large, the search was then narrowed down by focusing only on the keywords, reducing the count to 5,686 articles. To ensure a particularly innovative and recent focus, only articles from 2021 to 2024 were selected, yielding 2.464 records. Further refinement was achieved by selecting the following subject areas: "Computer Science", "Business, Management and Accounting", "Decision Sciences", and "Economics, Econometrics and Finance", "Energy" narrowing it down to 1.753 records. Subsequently, the number was restricted to 1.169 by excluding these keywords: "Office Buildings", "Heating", "Battery", "Housing", "Humans", "Digital Storage", "Air Conditioning", "Article", "Building", "Brain", "Electric Vehicle", "Electric Vehicles", "forestry", "Temperature", "Human", "Buildings", "HVAC". Then only papers published on journal (657) in English (644). 71 were unavailable, and the other papers have been carefully screened. 72 were selected, identified as those most relevant to the context.

TABLE I. KEYWORDS

"Forecasting" OR "Prediction" OR "Demand Forecasting"	General string to set the topic on forecasting	2.684.750
"Models" OR "Methods" OR "Alghoritms" OR "Planning" OR "Artificial intelligence" OR "Machine Learning" OR "Deep Learning" OR "Neural Network"	Focus on AI models	2.005.767
"Energy consumption" OR "Energy demand" OR "Energy production"	Focus on energy sector	20.389

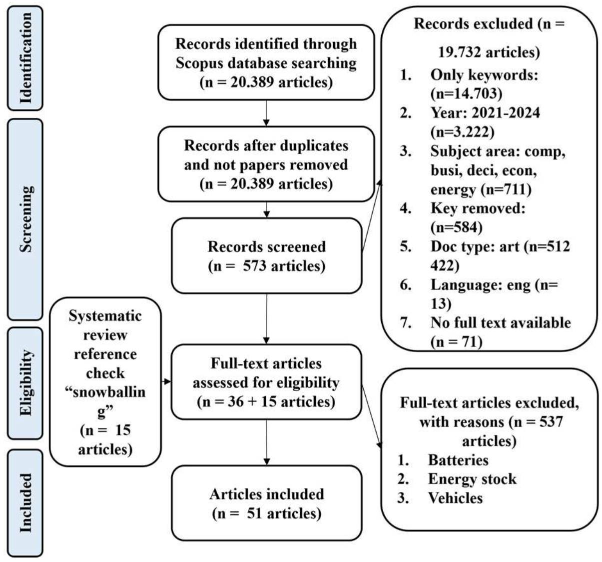

Fig. 1. PRISMA scheme

IV. Background

Cognitive Computing refers to the ability of machines to learn and it is generally called artificial intelligence [18]. These platforms include machine learning, reasoning, natural language processing, speech and object recognition, and narrative generation. Cognitive computing contains Machine Learning, Deep Learning and Grey models. Grey models is a technique for uncertain problems and require small data set to work [19], [20].

V. Literature review

In the context of time series analysis and demand forecasting, models based on artificial neural networks (ANN), convolutional neural networks (CNN), recurrent neural networks (RNN), and linear regression are widely used to provide accurate and useful predictions. Each model has its unique characteristics and specific applications, which can be adapted to the demand forecasting needs in various contexts [21]. Deep learning got a lot of interested in forecasting [1].

A. Short Term

Current forecasting methods do not distinguish between different energy consumption nodes and provide a global forecast, leading to poor prediction of target nodes. Additionally, complex production systems have thousands of machines with intricate interconnections of flows, making it difficult to manage the space of energy consumption nodes. The time series data of consumption present non-stationarity and non-linearity, negatively affecting short-term forecasts.

In [22], a spatio-temporal deep learning (ST-attention) to improve short-term forecasting accuracy in production systems, uses Convolutional Neural Networks (CNN) for spatial feature extraction, Gated Recurrent Units (GRU) for temporal feature extraction, and Attention Mechanism to dynamically weigh energy consumption nodes based on their importance.

Financial costs and environmental impacts of energy production, such as the greenhouse effect, requires cheaper and cleaner energy sources [11]. For short-term energy consumption prediction with data from smart meters, Graph Convolutional Recurrent Neural Network (GCRNN) combines Graph Convolutional Networks (GCN) and Long Short-Term Memory (LSTM) to extract spatial and temporal information simultaneously, capturing the consumers’ relationships [23].

Most forecasting methods have been developed to predict single or small groups of time series. Deep learning model based on LSTM, CNN can deal with time series with unequal lengths, big challenge in forecasting as data might not have been collected or observed up to a certain point but not beyond. In [24] a global model based on CNN, LSTM, and auto-encoders for multi-time series energy forecasting has been proposed, using a dataset from Brazil, reducing complexity and computational costs.

Complexity of both linear and non-linear models and lack of interpretability or the poor generalization capability can limit forecast power [17], [25]. Random Forest, Long Short Term Memory (LSTM), Deep Neural Networks (DNN), and Evolutionary Trees can be combined using Gradient Boosting and Extreme Gradient Boosting (XGB) techniques, reducing the training time and offering higher accuracy, 39% reduction in the Root Mean Square Error (RMSE) [17].

In [26], a data-driven moderation approach is proposed using a Batch Normalized Long Short-Term Memory network (BN-LSTM). The BN-LSTM approach helps in effectively forecasting and reducing energy consumption of industrial robots by leveraging the strengths of both LSTM cells and batch normalization. The system shows 56.74% improvement in performance compared to 1D-ResNet14 model. Moreover, with Yaskawa polishing movement dataset, had an average accuracy of 99% in forecasting energy consumption [26].

in [27], a model based on Gaussian Process (GP) estimator and trained using historical load series starting from 1990 forecasts the electric load demand during Holy Week, which presents unique challenges due to the variability of the date and the behavior of demand compared to normal working days. One of the main challenges in load forecasting is represented by extraordinary events known as intervention events.

In [28], a Short-Term Load Forecasting (STLF) model with transfer learning (TL), which allows the transfer of knowledge from similar time series to improve forecasts, and feed-forward NN is trained with 27 time series, representing the national electricity demand in European countries. It was shown that TL allows for more accurate forecasts and faster model training compared to the conventional NN approach.

Accurately forecasting quarterly or monthly energy consumption, characterized by small samples and nonlinearity, remains a challenge [29]. In [30], a model integrates machine learning and grey system theory. Grey relational analysis filter influencing factors on the object. The vector regression model describes the relationship between the object and influencing factors. The difference equation forecasting model predicts future values of influencing factors. This solution outperforms existing methods, confirming its effectiveness in accurate energy forecasting even with limited data and nonlinearity [30].

Distributed generation based on Renewable Energy Sources (RES) must match production and consumption, optimizing to avoid potential over-sizing or under-sizing, regardless of the application field. In [31] a regression model, the k-Nearest Neighbors (k-NN) algorithm is applied beyond local energy systems based on RES to include the design and evaluation of Demand Response programs, identifying energy savings opportunities, and creating tailored offers from energy suppliers. The method performs worse on error metrics that evaluate the identity of the predicted load profiles compared to the actual ones, while better performance is achieved in error metrics that measure consumption statistics [31].

The significant increase in energy consumption is also due to the growth of urban development, in the USA it accounts for 39% of total consumption [3], and the proliferation of smart buildings due to IoT [32]. However, smart energy solutions based on IoT have not been sufficiently integrated with traditional forecasting methods. In [33] a short-term forecasting system based on Convolutional Neural Network (CNN), Grasshopper Optimization Algorithm (MOGOA) and Deep Extreme Learning Machine (DELM) with Random Forests reduces delays and computational burden on centralized servers by using flow analysis methods and databases. Experimental results show an accuracy of 85%.

The traditional grey model has been widely used for short-term energy consumption forecasting with small data samples [19], [20], but its accuracy is affected by data fluctuations [20]. To overcome this challenge, [34] introduces the concept of wavelet de-noising, a data preprocessing process aimed at reducing unwanted fluctuations, leading to the creation of a new modified grey model defined as WD-TBGM(1,1), trained with 1000 simulations to ensure reliability. The results show that WD-TBGM (1,1) outperforms other forecasting models, including the traditional GM (1,1), BGM (1,1), and GPRM (1,1).

In table II the resume of the most important papers on short-term forecasting is reported.

TABLE II. SHORT-TERM STUDIES

Ref	Problems	Solutions
[22]	Lack of distinction between energy consumption nodes	Use of hybrid deep learning methods
	Difficulty in managing the complexity of production systems	Incorporation of attention mechanisms
	Lack of consideration for spatial and temporal relationships	Consideration of relationships between auxiliary nodes and targets
[26]	Complexity in modeling industrial robot (IR) consumption	Data-driven approaches (BN-LSTM models)
	Difficulty in identifying dynamic parameters	Use of Batch Normalization
[28]	Complexity in using time series for energy consumption	Transfer Learning (TL)
	Limitations of conventional models	Use of neural network (NN) models and TL techniques
[30]	Use of univariate models and instability of models	Integration of machine learning and grey system theory
	Lack of treatment of seasonality	Use of SARIMA models to capture seasonal trends
[31]	Difficulty in collecting detailed consumption data	Use of data-driven approach to predict load profiles
	Complexity in assigning load profiles to unobserved users	Use k-nearest neighbors (k-NN) method to map bills to typical load profiles
[24]	Need for accurate energy consumption forecasting	Combination of CNN, LSTM, and autoencoder models
	Time series with unequal lengths	Introduction of a global model that can be trained on series of different lengths
[33]	Difficulty in predicting energy demand	Creation of an IoT-based model using a multilayer perceptron with CNN algorithm features
	Need to optimize IoT system efficiency	Implementation of a semantic approach to data management and creation of a unified database structure
[23]	Limitations of existing models	New neural architecture called Graph Convolutional Recurrent Neural Network (GCRNN)
	Dependence on additional environmental variables and high dimensionality of data	Model removes dependence between variables and produces informative representations without increasing dimensionality
[17]	Limitations of existing models and lack of interpretability and generalization	Use of Stacking Ensemble model and combination of diverse base models (LSTM, DNN, Random Forest)
	Dependence on linear approaches and need for accurate forecasting	Dependence on linear approaches and need for accurate forecasting
[27]	Variability in load profile during Easter Week	Use of a day-ahead short-term predictor utilizing Gaussian Process
[34]	Data fluctuations	Introduction of Wavelet de-noising and hybrid model WD-TBGM (1,1)
	Small sample size and lack of adaptability	Applicability to small data samples and parameter optimization

B. Long Term

Long term electricity usage is very important and it is affected by environmental parameters and the day [35]. An electricity prediction model is a crucial part of the smart grid to enable predictive maintenance and self-healing responses to system disturbances, accommodate distributed energy sources, automate maintenance and operations, and reduce energy consumption [3]. A deep learning model for time series forecasting is proposed in [36] and considers the prediction outcome and predicts energy consumption. It consists of prediction encoder, explanation encoder, prediction decoder, and explainer.

The increase in industrialization has led to a growing use of electricity, which contributes to current environmental problems such as climate change. It is estimated that temperature-regulating equipment, such as heating, ventilation, and air conditioning systems, accounts for 40-50% of total energy consumption [3]. Predicting energy demand plays an important role in devising energy development plans for cities and countries. Available data on energy demand usually consist of a nonlinear real-valued sequence. In [3], a grey prediction models, without statistical assumptions by using data intervals to represent uncertainty in energy demand forecasting showed that the proposed grey-prediction-based models using functional-link nets to modify residuals performed well compared to other interval grey prediction models [3].

To address these issues, the Smart Grid has been developed [32], [37], an energy management system composed of 7 distinct areas: markets, operations, service providers, large-scale production, transmission, distribution, and consumers. A deep learning model, using the Kullback-Leibler divergence to refine data representation, incorporating temporal information to explain predictions based on the characteristics of the time series, is presented in [38].

Long-term forecasts play a vital role in multiple contexts, from anticipating future consumption of resources such as energy, water, and food to predicting the impacts of extreme weather events and natural disasters on infrastructure and security [8]. The critical flaws of most existing Transformer-based models are high computational cost of self-attention and lack of awareness regarding the importance of temporal order in time series forecasting, especially for long-term predictions. In [39], a deformable-local aggregation (DL) mechanism allows the model to dynamically adapt the size of the temporal aggregation window based on local information, improving the ability to discern complex temporal patterns, leading to accurate predictions [39].

Accurate energy load forecasting can facilitate effective energy distribution and avoid energy waste, reducing costs. In [40], LSTM-Informer model is used for long-term load forecasting. The lower layer of the model uses LSTM as a learning device to capture the short-term temporal correlation of the power load, while the upper layer uses the Informer model to address the problem of long-term dependency in power load forecasting. 1-year datasets of the distribution network of Tetouan, Morocco, showed that LSTM-Informer model has advantages in long-term power load forecasting compared to the advanced baseline method.

In [2] is presented Long Short-Term Memory (LSTM) model optimized by a hybrid optimization algorithm called Dipper-Throated (DTO) and Stochastic Fractal Search (SFS), named DTOSFS. IoT plays a crucial role by connecting physical and virtual devices. The proposed model improves model performance by adjusting its parameters to increase prediction accuracy. A publicly available dataset containing 121.173 measurements collected over 10 years in the USA was used showed that the model achieved a lower MSE compared to other methods [2].

In [41], M-ABC (Modified Artificial Bee Colony) is introduced to estimate medium and long-term energy consumption in Turkey. To validate the effectiveness of the method, 2 mathematical models were developed, one linear (M-ABCL) and one quadratic (M-ABCQ), using demographic and economic data, such as population, GDP, and trade data, which were considered as input parameters to estimate energy demand. The performance was compared with Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), and a hybrid approach that combines both (HAP). M-ABC resulted to be more accurate and can provide specific forecasts for Turkey's future energy demand up to 2025.

Another important aspect of energy forecasting is EECP, or "Electricity Consumption Forecasting for Households" [2], [42]. A metaheuristic based on an LSTM network and Butterfly Optimization Algorithm model is proposed in [43] to generate EECP forecasts.

Long-term forecasts of local, national, and international energy consumption are crucial components for policy of energy and economic growth. Energy consumption changes over time and non-linearly with income. The relationship between income and energy consumption also changes over time. Modern consumers use more electricity to their predecessor [7].

In table III the resume of the most important papers on long-term forecasting is reported.

TABLE III. LONG-TERM STUDIES

Ref	Problems	Solutions
[39]	Limitations of existing transformer-based models	Deformable-local aggregation (DL)
	Insensitivity to the order of time series	Introduction of positional weights and frequency selection module
[40]	Long-term power load forecasting	Use of LSTM-Informer model (combination of short-term and long-term models)
	Limitations of existing models like ARMA in handling non-stationary series	Integration of evolutionary algorithms such as ANN, RF, and GBM
[38]	Limitations of deep learning models in explaining the cause of forecasts	Proposed model integrates two encoders for explanation, one decoder for forecasting, and an explainer to identify significant attributes
	Limitations of models in explaining forecast results	Use of Kullback-Leibler divergence
[41]	Difficulty in accurately estimating energy demand	Introduction of new modified method based on artificial bee colonies (M-ABC)
	Need to improve forecast accuracy	Development of linear (M-ABCL) and quadratic (M-ABCQ) mathematical models
[7]	Variations in energy consumption and non-linearity with income	Use of functional coefficients and principal component functional analysis (FPCA)
	Need for models to capture the relationship between income and energy consumption	Forecasting estimated surface with non-parametric methods
[36]	Importance of load forecasting for energy consumption	Removal of outliers and expansion of data dimensions
[2]	Need for accurate forecasting and limitations of traditional methods	Use of DTOSFS algorithm to optimize LSTM model parameters, allowing more

		precise and efficient parameter tuning
[43]	Need for accurate prediction of energy consumption	Use of a metaheuristic based on LSTM network model
	Energy consumption forecasting can be influenced by a variety of non-objective factors	Use of Butterfly Optimization Algorithm to select optimal values

VI. RESULT AND DISCUSSION

Various models can be employed to predict future trends in energy demand. Literature on energy markets is however underdeveloped and tends to focus more on residential consumption. This is a significant limitation, especially considering the complexity of the global energy landscape [24], [26], [42]. Forecasting energy consumption is a critical challenge for environmental sustainability, further complicated by the complexity of time series data, resulting in inadequacies or inaccuracies [17], [42].

Another critical aspect is data availability, which is often uncertain, imprecise, and subject to fluctuations [29]. These data, essential for generating accurate forecasts, are influenced by many unpredictable variables, such as climate variations or economic fluctuations. This is particularly problematic in an era where sustainability and energy efficiency are central to global policies [2], [3], [4], [6].

To address these challenges, it is crucial to explore and implement more advanced models. In recent years, new models have been introduced that offer greater accuracy in forecasts. Among these, Machine Learning models [30], Neural Networks [22], [23], [33], Deep Learning [1], [17], [22], [33], [36], [38], and Grey Models [3], [19], [20], [30] are emerging as fundamental tools. AI-based optimization algorithms can explore various energy sources combinations and management strategies to determine the most effective solution, considering operational, economic, and environmental variables.

The benefits of more accurate energy forecasting include significant economic savings and a reduction in carbon dioxide emissions [2], [3], [4], [6]. Optimal use of energy resources reduces reliance on costly and polluting traditional sources, improves the operational efficiency of companies, and enhances their reputation as environmentally responsible enterprises [8].

VII. CONCLUSION

This paper could then answer the RQs.

The 1st, *"What Are the Current Methods and Models for Demand Forecasting?"*, answer is that the most used models for demand forecasting are: **Machine Learning Models**, using various algorithms to analyze historical and current data to predict future demand; **Neural Network Models**, designed to recognize complex patterns and relationships in data, often applied for both short-term and long-term forecasts; **Grey Models**, handling systems with incomplete or uncertain information and are useful in complex forecasting scenarios. These models can be applied to forecast energy demand over both short and long periods.

The 2nd, *"How Can Industry 4.0, and Particularly AI, Assist in Forecasting?"*, answer is that AI enhances forecasting accuracy in energy production and consumption through machine learning algorithms. Key benefits include: more informed and timely **decisions**; **optimized energy resources allocation** and reduction of **energy costs** and **CO2 emissions**; adaptation to **changes**, as AI can quickly adapt to changes in weather and operational conditions, providing updated and reliable forecasts; improved planning and **management** based on better forecasting, avoiding overproduction and energy shortages.

In summary, AI and Industry 4.0 contribute to more effective and efficient energy management by improving forecasting accuracy and optimizing resource use. Simulation, like Monte Carlo [44], [45], can be added to improve the quality of forecasting and AI training and to evaluate also the costing of energy [46]. IoT is another technology which, thanks to the ability to collect data [47], [48], [49], can be applied in many different sectors [50], [51].

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