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A Review of Deep Transfer Learning Strategy for Energy Forecasting

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ABSTRACT

Over the past decades, energy forecasting has attracted many researchers. The electrification of the modern world influences the necessity of electricity load, wind energy, and solar energy forecasting in power sectors. Energy demand increases with the increase in population. The energy has inherent characteristics like volatility and uncertainty. So, the design of accurate energy forecasting is a critical task. The electricity load, wind, and solar energy are important for maintaining the energy supply-demand equilibrium non-conventionally. Energy demand can be handled effectively using accurate load, wind, and solar energy forecasting. It helps to maintain a sustainable environment by meeting the energy requirements accurately. The limitation in the availability of sufficient data becomes a hindrance to achieving accurate energy forecasting. The transfer learning strategy supports overcoming the hindrance by transferring the knowledge from the models of similar domains where sufficient data is available for training. The present study focuses on the importance of energy forecasting, discusses the basics of transfer learning, and describes the significance of transfer learning in load forecasting, wind energy forecasting, and solar energy forecasting. It also explores the reviews of work done by various researchers in electricity load forecasting, wind energy forecasting, and solar energy forecasting. It explores how the researchers utilized the transfer learning concepts and overcame the limitations of designing accurate electricity load, wind energy, and solar energy forecasting models.

INTRODUCTION

Nowadays, energy forecasting is the foundation for engineering and scientific researchers worldwide in energy sectors. The population increase will reach 9.8 billion in 2050; hence, the electricity demand will also exceed 38000 terawatt-hours every year (Veers et al. 2019). The energy demand increases with the increasing population. It imposes the necessity to forecast the energy demand in advance to sustain the economic growth of the country globally (Subbiah & Chinnappan 2020a). Electricity load, solar power, wind speed, and wind power forecasting are a part of energy forecasting. Many researchers have achieved this by developing various models using different technologies and considering various factors. The existing methodologies assume the dataset has sufficient data for training the model (Subbiah & Kumar 2022). In reality, sufficient data is unavailable for designing the forecast model in the newly built plants. To overcome this limitation, a transfer learning strategy is introduced that transfers the knowledge from the pre-trained model of a similar domain where sufficient data is available. It is hard to make sufficient data for energy applications due to the two main challenges. One is the difficulty in accessing high-quality real-time data in large volumes; another is the possibility of negative knowledge transfer to the target domain from the source domain. Generally, energy forecasting is categorized into four major types: long-term, medium-term, short-term, and very short-term energy forecasting based on the forecasting duration (Subbiah & Chinnappan 2020b, Zor et al. 2017). Types of energy forecasting based on time horizon are shown in Table 1.

Energy forecasting is an important research area in the modern electric world. While searching the Scopus database with the keyword "energy forecasting" in the title, abstract, and the keyword of the documents indexed, it shows 35970 documents indexed from 2015 to 2022. It represents the number of documents indexed increases every year in Scopus 2603, 2998, 3299, 4035, 4881, 5157, 6010, and 6987 documents indexed in 2015, 2016, 2017, 2018, 2019, 2020, 2021, and 2022, respectively. Compared to 2015, there is a double of documents indexed in 2022. It represents the growing trend of research papers in the energy sector. Fig. 1 shows

Table 1: Types of energy forecasting based on time horizon.

S. No.	Types of Energy Forecasting	Duration
1.	Very Short Term Energy Forecasting	A minute to an hour
2.	Short Term Energy Forecasting	An hour to a week
3.	Medium Term Energy Forecasting	More than a week to a year
4.	Long Term Energy Forecasting	More than a year

the number of documents indexed in the Scopus database yearly. It demonstrates the significance and demand of energy forecasting.

In recent days, electricity load forecasting has been a trending research field. It is essential to sustain the reliability and the smooth functioning of the power system by balancing electricity demand with supply (Nazari-Heris et al. 2022). The electricity demand increases with the increase in population. Forecasting electricity demand is mandatory to satisfy the electricity demand with the supply (Fawaz et al. 2018, Subbiah et al. 2023, Weber et al. 2021). In electricity load forecasting, very short-term load forecasting represents a minute to an hour level forecasting. It is essential for controlling automatic electricity generation. Short-term load forecasting represents more than an hour to a week level forecasting (Subbiah & Chinnappan 2022b). It is useful for making the unit commitment and economical electricity dispatch plans in the power system. The medium-term load forecasting represents more than a week-to-month level of forecasting (Subbiah & Chinnappan 2022c). It is important for the preparation of effective scheduling of fuel requirements, electricity generation, electricity transmission, and electricity maintenance (Kumar 2017). Long-term electricity load forecasting represents more than a month to a year (Subbiah & Chinnappan 2020b, Subbiah & Chinnappan 2021). It is essential for the installment of the new power plants and also for the extension of the power systems.

The accurate load forecasting of any region is achievable with the history of load demand and the correlated features to load in large volumes without any incompleteness (Yin et al. 2021). However, these details are not available completely for all the regions in the real world. In such cases, the transfer learning-like concepts can be applied to forecast the accurate load for those regions by transferring the knowledge from other models of similar regions where the complete details are available (Chen et al. 2021). The time series load has an intrinsic time-varying behavior. So, there may be much variation among the historical and new data. It has only one temporal dimension. The recorded load data from different domains can share some common features. So, the models constructed for one problem with large data can be adaptable to the different related problems with limited data in load forecasting.

In the modern era, energy from solar and wind sources is an important renewable energy source. Solar and wind energy generation increases due to its dramatic benefit of maintaining a pollution-free society and securing the environment by reducing carbon emissions and considering the depletion of fossil fuels. The developing countries also started to release a plan for future energy demand using renewable energy sources like solar and wind (Oh et al. 2022). Many governments have started investigating clean and green renewable energy sources due to the rapid global

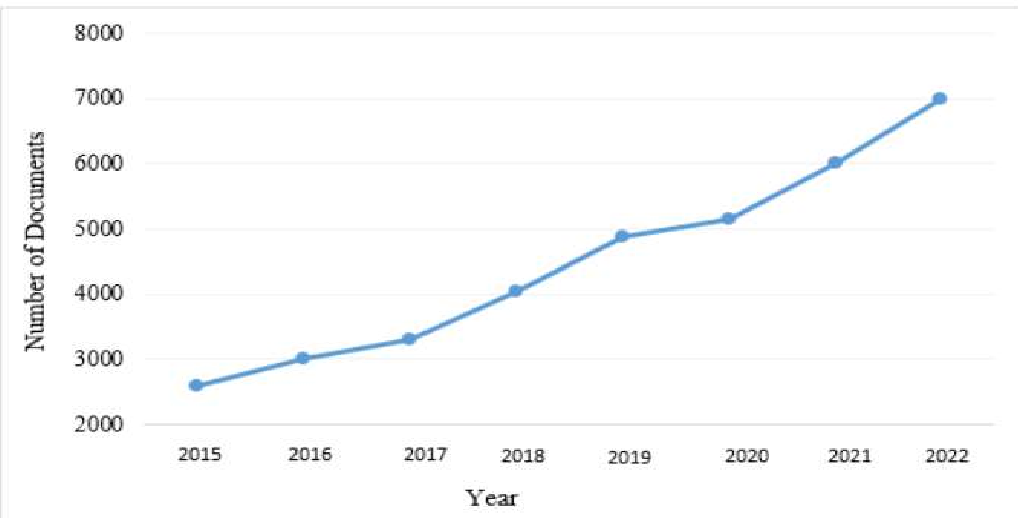

Fig. 1: Number of energy forecasting documents from 2015 to 2022.

warming and weather changes. Wind and solar energy sources got special attention for satisfying future energy demands naturally (Manandhar et al. 2023).

Wind energy is a widely utilized energy source. Wind energy has a volatile and uncertain nature. So, the accurate prediction of the wind energy depends on the accurate wind speed prediction (Yin et al. 2021). Researchers utilize physical, conventional, and artificial intelligence models for wind speed forecasting. They produced good prediction results when sufficient data was available for training the models (Ye & Dai 2018). With limited data, the performance of these models is poor. The newly built wind form has no historical data for predicting wind speed.

Similarly, some wind farms may have incomplete and less quality data. So, the researchers utilized the transfer learning concepts to forecast the wind speed for the newly built wind farm and the poor data wind farm. Transfer learning is a powerful concept used to train the new model for related real-world problems. It transfers the knowledge learned from the already trained models to build a model for another different but related problem (Hu et al. 2016).

Solar energy is a powerful alternative to conventional sources of energy nowadays. The earth receives an average of 1367 $W.m^{-2}$ of solar irradiance. It can be utilized to produce 1.74 × 1017 W yearly. This energy is sufficient for global residential, industrial, and commercial requirements. So, solar energy is important in satisfying future energy demand (Kumari & Toshniwal 2021). The planning of the solar plant photo-voltaic (PV) energy production necessitates accurate power demand in advance. People moving towards cities increases the population in urban areas. It triggers the urban areas from moving gradually into smart cities. Digitization is mandatory for automating life in smart cities. It increases the electricity demand, increasing the demand for electricity forecasting. Global warming introduces a new source like solar for electricity generation. The non-conventional solar power generation secures life in smart cities by reducing carbon emissions and utilizing solar energy for power generation. It also provides a pollution-free environment and protects human life in urban areas (Sarmas et al. 2022). Solar panels and plants can be installed easily in domestic neighborhoods to meet this energy demand with supply. The solar power plant utilizes solar radiance as an important parameter for determining photo-voltaic power. The solar radiance depends on meteorological variables (Kumari & Toshniwal 2021). Considering weather factors with PV power data guarantees improved solar power generation forecasting.

SIGNIFICANCE OF TRANSFER LEARNING

Recently, transfer learning emerged as a powerful strategy for training the new model to related real-world problems (Hooshmand & Sharma 2019). The Scopus database shows the significance of transfer learning. The last five years data from Scopus represents the rise of research documents in energy forecasting using transfer learning every year linearly. The search was done on Scopus to find many research documents indexed with the keywords "energy forecasting" and "transfer learning" in the title, abstract, and keyword. The search result provides 327 documents indexed from 2018

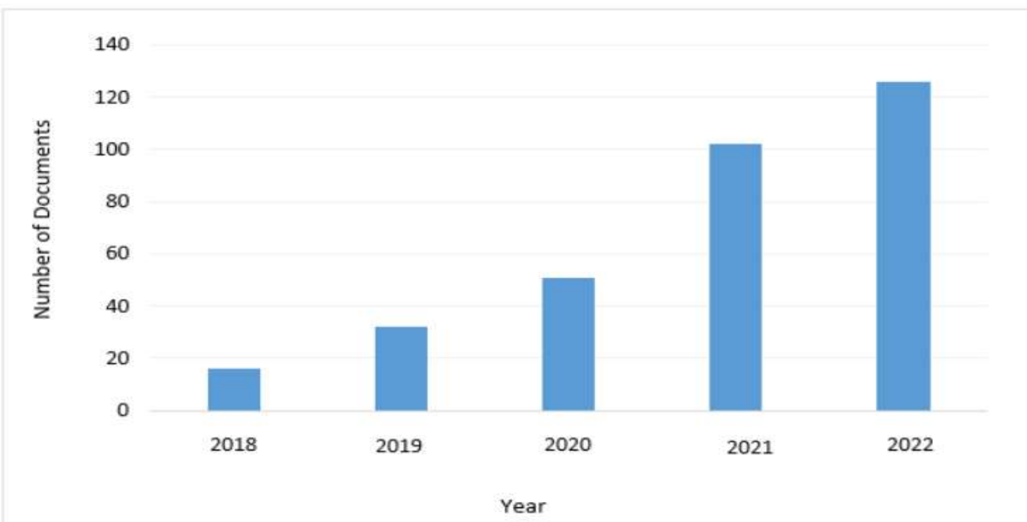

Fig. 2: Number of energy forecasting with transfer learning documents from 2018 to 2022.

to 2022. The number of papers indexed in 2018 is 16. But the papers indexed in 2019 show 32, which is the double of 2018. In 2020, 51 papers were indexed, and in 2021, 102 papers were indexed. In the last year, 2022, 126 papers were indexed. It is graphically shown in Fig. 2.

The Scopus database shows more documents published by China for energy forecasting using transfer learning, followed by the United States and India. The number of documents published by different countries is shown in Fig 3. The transfer learning strategy transfers the knowledge learned from already trained models to build a model for another different but related problem (Ye & Dai 2018, Tian et al. 2019, Qureshi et al. 2017). Fig. 4 shows the representation of transfer learning. It represents the knowledge transfer from the model developed using a large amount of data to the model that has to be trained using limited data (Peng et al. 2022). Transfer learning can be applied in two ways, namely, the pre-trained model approach and the developed model approach. These models can be applied to the new problem and attain effective predictive analysis. The pre-trained model approach helps to use the already trained model fully as it is or as part of the trained model, or it tunes the trained model for solving related other real-world problems easily. The pre-trained model approach is classified into three types: selecting the model, reusing the model, and tuning the model (Fawaz et al. 2018).

The selecting model approach selects the best model from the already trained model pool. The reusing model approach uses the already trained model of the related problem as the initial point for the next problem. It may reuse the entire or part of the model in the second problem. The tuning model approach tunes the already trained model to optimize or generalize it for the next related problem. The developed model approach identifies a similar problem with enormous data and exhibits a strong relation with the input, output, and concept. Then, it develops a better model for that problem. After that, it uses this developed model for the new problem as it is or tunes some parameters in it and then applies for the new problem. Ye & Dai (2018) utilized the transfer learning concepts in time series forecasting. Fawaz et al. (2018) used Dynamic Time Wrapping (DTW) to find the similarity between the source and target data to select and transfer knowledge from the strong source data.

The selection of transfer learning strategies relies on data availability, the task, and the application domain. The strategy selection answers what part of knowledge to be transferred, when to transfer that knowledge, and how to transfer that knowledge to a similar new problem. Traditional transfer learning is categorized into three types, namely, inductive, transductive, and unsupervised transfer learning. The inductive category of transfer learning is well applied to problems with the same source and target domains. It transfers the learned knowledge from source to target for improving the target model instead of starting the learning from scratch. Transductive learning is applied to the problem with different but interrelated source and target domains. Hence, the source domain has many labeled data, whereas the target domain only has unlabeled data. Unsupervised learning is almost the same as inductive learning. But, it

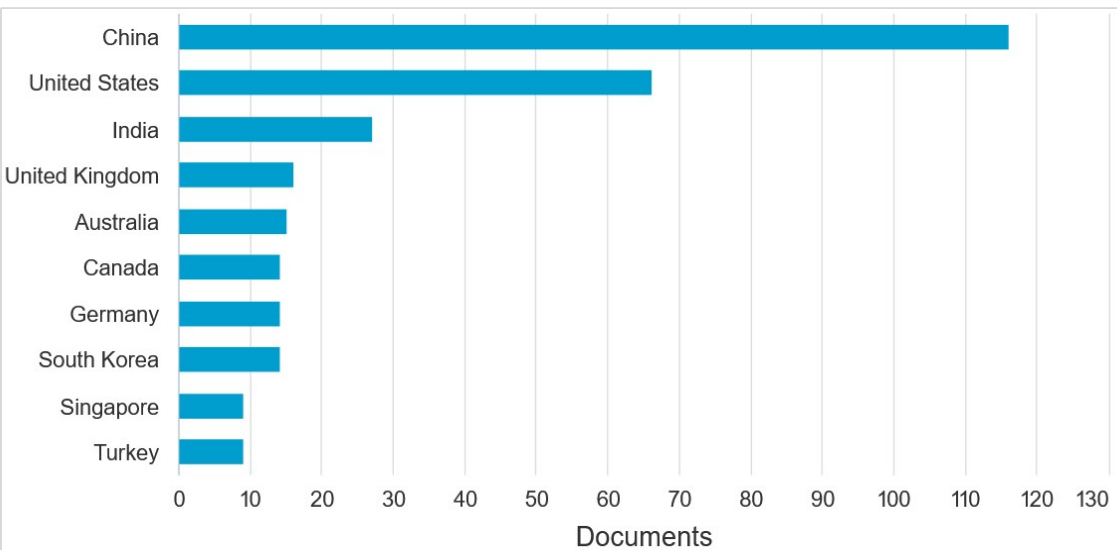

Fig. 3: Comparison of the number of energy forecasting with transfer learning documents from the Top 10 countries (2018 to 2022).

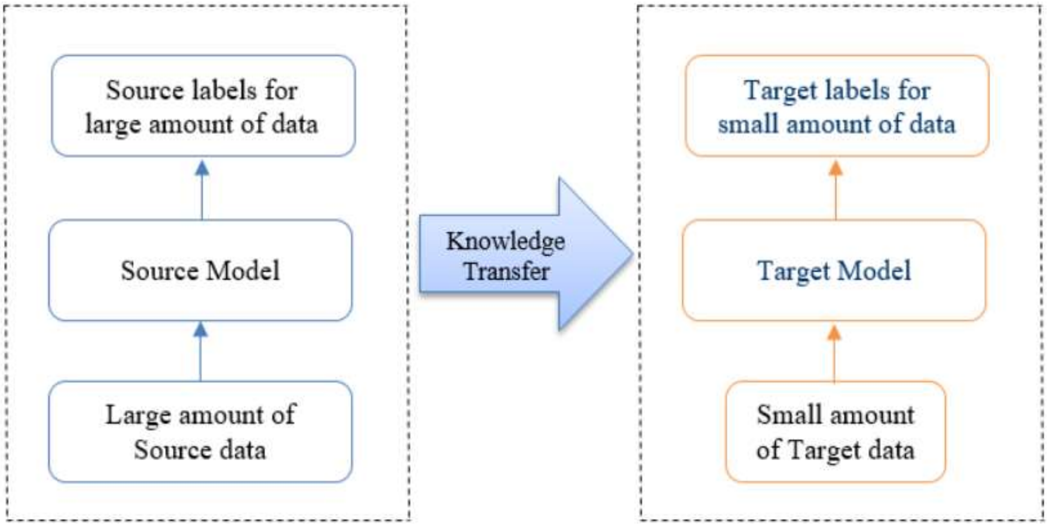

Fig. 4: Representation of transfer learning.

involves the unlabeled data in both the source and target domains (Tian et al. 2019).

Generally, there are two types of transfer learning, homogeneous and heterogeneous, depending on the dependency of the source and target domain samples and the similarity between the domains. The homogeneous type of transfer learning is applied to the domains with the same feature space but a small difference in their marginal distributions. It may follow instance transferring or parameter transferring, feature representation transferring, or rational knowledge transferring techniques from source to target for better target domain model performance. The instance transfer is done at an instance level from a source with large data and a target with limited data.

The parameter transfer is done at the model or parameter level from source to target. It creates many source learners and optimizes them by combining them like an ensemble method, and finally, it uses this learned knowledge to enhance the target learner's performance. At the feature level, the feature representation transferring is performed. It transfers the features from the source to the target or transforms the source and target features to the common feature space and then uses these features for the target domain. Rational knowledge transfer utilizes the source and target domains' relationship to transfer knowledge (Wu et al. 2022). It transfers the relationships learned from the source as a rule to the target domain. Heterogeneous transfer learning is applied to perform the interrelated or cross-domain task in the target domain (Hooshmand & Sharma 2019, Jin et al. 2022).

Machine learning with a transfer learning process enhances the learning process and model performance compared to machine learning without transfer learning (Ye & Dai 2022). The learning models are constructed by learning only the set of data provided as an input to that model. The constructed model becomes inefficient if the data is limited and incomplete (Kumar & Lopez 2016b). On the other hand, machine learning with the transfer learning concepts constructs an efficient model. First, the model with sufficient data is constructed. This is followed by the knowledge being transferred from the constructed model to the new one, which has insufficient information for training. Thus, the new model is constructed by getting information from the old model. The knowledge is transferred from the pre-trained model to the newly constructed model using the transfer learning concept. Thus, transfer learning with machine learning helps to build the electricity load forecasting, wind speed forecasting, wind power forecasting, and solar power forecasting models and also improves the performance of the forecasting models where insufficient data is available (Lu et al. 2022, Subbiah & Chinnappan 2022a).

APPLICATIONS OF TRANSFER LEARNING

Transfer learning provides many benefits in developing machine learning and deep learning models. It is especially useful for saving resources and improving the efficiency of the model construction when a new model is trained (Gao et al. 2020, Khan et al. 2022). It can develop an efficient model with unlabeled data. Hence, every new model construction does not require a dataset with labeled data. A large volume of labeled data collection is required for accurate decision-making. But, in general, many applications in real-time suffer from limited labeled data. In such a case, transfer learning helps develop the model using sufficient labeled data and then applies the same model to limited unlabeled data. Likewise, it helps a lot to save the training time of the model.

Similarly, constructing the learning model for complex real-time problems is tedious. Transfer learning helps to reduce this complexity by using a similar pre-trained model or simply taking it from scratch and redefining it. So, the knowledge can be transferred from the pre-trained model to the new model. Thus, the developers and decision makers take the knowledge from different models to fine-tune the model for the specific new problems easily (Jin et al. 2022). To enhance the new model, the parameters can also be transferred from the already developed models to the newly constructed ones (Hu et al. 2016).

The applications of transfer learning also include image classification, gaming, sentiment analysis, spam filtering, natural language processing, computer vision, the autonomous driving industry, the healthcare sector, the energy sector, and the e-commerce industry (Cao et al. 2018, Karmel et al. 2018, Kiruthika et al. 2014, Kumar 2019, Kumar & Lopez 2015, Kumar & Lopez 2016a, Swaroop et al. 2014). In recent research, the transfer learning concept was widely utilized in image recognition tasks. In image classification, the neural network is trained using many images to identify objects effectively. But it is a tedious and time-consuming task. The introduction of transfer learning greatly reduces the training time of the neural network by pre-training the model using ImageNet. Especially in medical image processing, kidney problems are identified from the ultrasound images by pre-training the CNN using ImageNet. Likewise, the model constructed using MR scans can be utilized for analyzing the CT scans. Transfer learning is also footprinted in gaming applications to develop new games easily by utilizing the pre-trained model of the existing game. Whenever a new game is developed, it is necessary to learn new algorithms and techniques for the new game. The transfer learning helps to understand the tactics learned from the older version or the existing game similar to the new game. In sentiment analysis, transfer learning analyzes customer behaviors and sentiments well. From the social media posting, the emotions of the customers are learned and transferred to analyze the behavior of the customer (Gomez-Rosero et al. 2021, Paramasivan 2021, Sivasankari & Baggiya Lakshmi 2016, Wang et al. 2020,). Solar panel defect detection can also be done by processing the solar panel images using MobileNetv2, ResNetv1, and inceptionv3 with pre-trained models (Zyout & Oatawneh 2020). Building the forecast model with limited samples may not provide an accurate result in energy forecasting. Similarly, the newly built plants do not have the historical data for training and building the forecast model. The transfer learning strategy is a gracious gift for the researchers to enhance the accuracy of energy forecasting with limited data.

TRANSFER LEARNING IN LOAD FORECASTING

In the modern era, many researchers released the electricity load forecasting models for the newly built power plants using transfer learning concepts. This section reveals the research using the transfer learning concept for electricity load forecasting. Zhang & Luo (2015) presented short-term load forecasting using the Gaussian process and transfer learning. It introduces the automatic source task selection algorithm for finding the suitable source task for the target task. It experiments on the 12 nearby cities of Jiangxi province of China power load data. The presented model performs better and reduces the computational complexity by using the transferred knowledge from neighboring cities, avoiding transferring negative knowledge using the source task selection algorithm and replacing matrix inverse operations with smaller matrix orders. Lu et al. (2022) introduced the model using mixup and transfer learning concepts for short-term load forecasting. It performs the data enhancement using a mixup and avoids overfitting using transfer learning. It transfers the load of the users whose consumption load patterns are the same and enhances the generalization capability of the load forecasting model. The similarity of the load patterns is identified using the maximal information coefficient (MIC), and the forecasting was done using long short-term memory (LSTM). The simulation results showed that the deep learning-based LSTM model and a transfer learning concept proved better in forecasting the short-term load.

Jung et al. (2020) presented a monthly load forecasting model using a deep neural network. The authors enhanced the forecasting accuracy by adapting the transfer learning strategy. The experiment was done in a Tensorflow 1.13.1 environment using 14 years of monthly electricity load of 25 districts in Seoul. The population, weather, and calendar features are considered along with load data. Pearson Correlation Coefficient (PCC) extracts similar load patterns from other district datasets.

Consequently, load forecasting was done using deep neural network (DNN) with the top 10 similar domain transferred data, DNN with the top 20 similar domain transferred data, and DNN with the top 30 similar domain transferred data. The result shows that the DNN with the transfer learning attained an improved forecast compared to baseline DNN, Random Forest (RF), Multiple Linear Regression (MLR), and Extreme Gradient Boost (XGB). Jin et al. (2022) developed a model for predicting short-term load using transfer learning concepts in deep learning. The parameter-based transfer learning is introduced in the hybrid convolution neural network-gated recurrent unit (CNN-GRU) model for improving load forecasting results. The knowledge from the model trained using the large dataset was transferred to the training model of the smaller dataset for performance enhancement. The solve-the-equation was utilized to find the data distribution bandwidth. The experiment used five years of commercial profile data from South Korea recorded hourly and one-year residential profile from the United States recorded hourly. The result shows that the CNN-GRU with transfer learning model outperformed back propagation (BP), LSTM, CNN-LSTM, Linear Regression, and GRU models.

Table 2: Transfer learning in load forecasting.

Sl. No.	Author	Dataset	Methodology	Remarks
1.	Jin et al. (2022)	Commercial profile, South Korea (Hourly), Residential profile of United States	CNN-GRU with transfer learning (Parameter-based)	Parameter-based transfer learning solved limited data issues in the CNN-GRU model and guaranteed improved accuracy and reliability.
2.	Jung et al. (2020)	25 districts monthly electric load in Seoul	Pearson correlation coefficient (PCC) + Deep neural network (DNN)	DNN with PCC transfer learning achieved better forecasting performance compared to basic DNN and other machine learning models MLR, RF, XGB
3.	Zhang and Luo (2015)	Power load data of Jiangxi province of China (12 cities)	Gaussian process model with source task selection algorithm. Transfer Learning Gaussian Process (TLGP), Multi-task Gaussian Process (MTGP), Auto Regression (AR), Support Vector Machine with Particle Swarm Optimization (PSO-SVR) and Artificial Neural Network (ANN)	Achieved better accuracy with reduced time complexity using knowledge transfer from the neighboring cities, avoiding the transfer of negative knowledge using source task selection algorithm and replacing matrix inverse operations with smaller orders of matrix
4.	Lu et al. (2022)	-	Mixup and Transfer learning concepts. Maximal information coefficient + long short term memory (MIC+LSTM)	LSTM with transfer learning enhanced the generalization ability and avoided the overfitting of the model
5.	Gomez-Rosero et al. (2021)	Ten houses load consumption data from London-Ontario	Deep neural network with similarity-centered architecture evolution search (DNN-SCAES)	DNN-SCAES achieved an improved accuracy compared to the feed-forward neural network, LSTM one shot, and vanilla LSTM
6.	Xu and Meng (2020)	USA (20 states) and Australia (5 states) electric load data	Time series decomposition-based hybrid transfer learning	A model with similar location data improved the electric load prediction by 30%. Negative transferring is also avoided by using time series seasonal decomposition.
7.	Lee and Rhee (2021)	Residential dataset: Korean Non-residential dataset: substation electric load dataset - UCI repository	Deep neural network with transfer learning and Model-Agnostic Meta-Learning (MAML)	DNN with transfer learning and MAML achieved better results than ARIMA, traditional individual learning approach, and one-for-all models (MLP, XGB, LSTM, Seq2Seq, and ResNet/LSTM).
8.	Ribeiro et al. (2018)	Energy consumption and weather data of 4 school buildings data for 3 years	Hephaestus- Novel transfer learning method	Hephaestus handled multi-feature time series data and improved the performance by 11.2% using other schools' data.
9.	Cai et al. (2019)	ISO New England, GEFCom 2012	Two-layer transfer-learning-based gradient boosting decision trees (TL-GBDT)	TL-GBDT achieved better forecasting results, especially with limited historical load data.
10.	Mocanu et al. (2016)	Load profiles of residential and commercial buildings: Baltimore Gas and Electric Company	Reinforcement and Deep belief networks (DBN) with cross-building transfer	Cross-building transferred knowledge with Reinforcement, and DBN achieved better forecasting accuracy
11.	Gaucher et al. (2021)	National Data: UK- Semi-hourly electricity, temperature and smart meter data	Generalized additive models and Random Forest	The transferring of the multi-scale information by aggregating the experts enhanced forecasting results.

Gomez-Rosero et al. (2021) developed the model for residential load forecasting. The authors handled the challenges of residential load forecasting by expanding the demand response program and using transfer learning concepts. The multiple household electricity load consumption data was utilized to forecast the neighboring house load consumption. It uses the evolutionary algorithm named similarity-centered neural architecture search. This evolution search keeps the centremost house load consumption patterns. Then, it adjusts the weight of each other houses in the multi-house collection from their neighboring houses. The experiment used electricity load consumption data from 10 houses in London and Ontario. The simulation results showed that the developed model improved performance for the large dataset compared to the feed-forward neural network, LSTM one shot, and vanilla LSTM.

Xu & Meng (2020) presented hybrid short-term load forecasting using decomposition and transfer learning concepts. After decomposition, the seasonal and trend components are processed using machine learning methods. The irregular components are handled by using the two-stage transfer regression model. The presented model handles the issues related to transfer learning well by avoiding negative transfers. It acquires knowledge from other locations' electric load data and improves the interpretation capability of the electric load time series seasonal cycles. The model handles well the scalability issues with the dataset. The model was tested using the USA (20 States) and Australia (5 States) electric load data. The result confirms that the model attained an improvement in forecasting accuracy. Lee & Rhee (2021) designed a deep neural network model with meta-learning and transfer-learning concepts to improve the short-term load forecast outcome. The authors designed and tested the model using the residential and non-residential electricity load data. The model improved compared to Autoregressive Integrated Moving Average (ARIMA), the traditional individual learning approach, and one-for-all models (multilayer perceptron, XGB, LSTM, Seq2Seq, and ResNet/LSTM). Table 2 shows the review of transfer learning in load forecasting.

TRANSFER LEARNING IN WIND ENERGY FORECASTING

Many researchers in the past decade developed wind speed forecasting models using physical, statistical, machine learning, and deep learning models. Hanifi et al. 2020 explored the related work done by researchers in wind power forecasting using physical, statistical, and hybrid models. Maldonado-Correa et al. (2021) reviewed the developed wind power forecasting models using artificial intelligence. Lee et al. (2020) designed a deep neural network using long short-term memory and proved that LSTM guarantees an improvement in the wind power forecast compared to SVR and ANN. Yang et al. (2021) designed a wind power prediction model that classified the turbines by introducing the fuzzy C-means clustering algorithm and predicted the wind power generation using power curves. The model reduced complexity and improved the prediction accuracy. Researchers utilize transfer learning strategies to improve wind speed and wind power forecasting.

This section reviews the related research work done by researchers in wind speed forecasting using a transfer learning strategy. Yin et al. (2021) introduced a network-based deep transfer learning model to forecast the multi-step wind speed. The author utilized the wind and meteorological data collected from six wind farms. The model extracts the temporal and meteorological features in the pre-training stage using CNN and LSTM. It is achieved by connecting many CNNs in parallel to the LSTM in a serial manner. It forms a serio-parallel CNNs-LSTM (CL) extractor. The sound-trained CL extractor parameters are partially transferred to the target wind farm at the transfer training stage. The crisscross optimization is also implemented to fully connect layer parameters. The deep learning models CNNs-LSTM with parameter-based transfer learning achieved promising forecasting results.

Hu et al. (2016) used DNN with a transfer learning strategy for designing a short-term wind speed forecasting model. First, the model is trained using the data from an existing data-rich wind farm. Then, the author transfers the details from the data-rich wind farms to the newly built wind farm to fine-tune the deep neural network. Chen et al. (2021) developed a short-term wind speed model using bidirectional gated recurrent units and parameter-based transfer learning. First, the model is pre-trained using large volumes of source wind farm data. Then, it was fine-tuned in the target wind farm with limited data using parameter-based transfer learning. As a result, the model achieved better wind speed forecasting accuracy for the newly built target wind farm in China with less training time.

Wang et al. (2020) introduced the wind speed forecasting model using Convolutional Neural Network (CNN) and Parameter-based transfer learning. It considered the special and temporal information between three wind farms in China. The CNN migrates the fluctuation in the wind speed, and the transfer learning strategy shares the trained model parameter to the newly built wind farm (limited data) from the wind farm, which has sufficient data. The result shows that the CNN with parameter-based transfer learning offers a better wind speed forecasting result than the kernel ridge regression, CNN, and SVR. Qureshi & Khan (2019) presented a short-term wind power forecasting model using adaptive transfer learning. The author transferred knowledge from different domains like wind speed and wind power and also from different regions. Hence, the author utilized the transferred knowledge for an effective weight initialization and better learning of the input for the deep neural network. The author proved the ATL-DNN model attained better forecasting results.

Liang et al. (2022) designed a wind speed forecasting model using the wind speed and meteorological data collected in one-hour intervals from 18 wind farms in Hebei province, China. The author constructed and trained the dilated CNN & BiLSTM model offline by fusing the multifaceted features. Then, the model was transferred to the new target wind farm, and the prediction was done online. The model performance is also improved by introducing the multi-objective grasshopper optimization algorithm during prediction. The author compared the model performance against the state-of-the-art baseline models and proved that transfer learning greatly helped improve wind speed forecasting accuracy. Table 3 summarizes the related work done in wind speed and wind energy forecasting with transfer learning.

TRANSFER LEARNING IN SOLAR ENERGY FORECASTING

Many researchers developed solar power forecasting models using physical and statistical models. After the introduction and advancement of artificial intelligence methods, machine learning models were introduced. Recently, deep learning-based deep neural network models were designed & forecasted for solar power generation. Researchers achieved better forecast results with deep learning models compared to other models. But still, there is a lack of achieving an accurate solar power forecast with limited data for training the models.

The transfer learning strategy strongly supports these kinds of limited data and training issues by transferring knowledge from other pre-trained models. Table 4 shows the review of transfer learning in solar power forecasting. Sarmas et al. (2022) developed a model for solar power forecasting

Table 3: Review of transfer learning in wind energy forecasting.

Sl.No	Author	Dataset	Methodology	Remarks
1.	Yin et al. (2021)	Six wind farms from Inner Mongolia and China	CNNs-LSTM with transfer learning	Spatio-temporal coupling details from the source wind form improve the forecasting performance of the target wind farm with limited training data. The deep learning model CNNs-LSTM with parameter-based transfer learning achieved promising forecasting results.
2.	Hu et al. (2016)	Wind Speed data from Ningxia, Jilin, Inner Mongolia, and Gansu	Deep neural network with transfer learning	Reduced the wind speed forecasting error for a newly built wind form by transferring the details to the new wind form from an existing wind farm using transfer learning.
3.	Chen et al. (2021)	Power and meteorological data from two wind farms in China (Zhejiang Province)	Bidirectional gated recurrent unit & Parameter transfer learning	Achieved a better wind speed forecasting accuracy for the newly built target wind farm in China with less training time
4.	Wang et al. (2020)	Wind speed data from China (3 commercial wind farms)	CNN & Parameter-based transfer learning	CNN with Parameter transfer learning offers a better wind speed forecasting result by learning the wind speed fluctuations and transferring the trained model parameters of the wind farm with sufficient data to the newly built wind farm.
5.	Cao et al. (2018)	Wind power data - China	Jaya Extreme Gradient Boosting (Jaya-XGBoost) with KNN	KNN selects highly relevant historical data from the neighboring wind farms. Jaya-XGBoost with KNN achieved better wind speed forecasting results than SVM, LASSO, and NN.
6.	Qureshi and Khan (2019)	Wind power and weather data from the European-Center of Medium-range Weather-Forecasts	ATL-DNN: Adaptive Transfer Learning in Deep Neural Networks	Attained better wind power forecast by transferring knowledge from different domains and regions.
7.	Liang et al. (2022)	Meteorological and wind speed data from 18 wind forms in Hebei province	CNN & BiLSTM with multifaceted feature fusion & transfer learning	The training is performed offline, and the prediction is performed online. The dilated CNN & BiLSTM learned the wind speed characteristics offline using multifaceted features, transferred the model, and improved the prediction accuracy using a multi-objective grasshopper optimization algorithm.

using Stacked Long Short Term Memory (Stacked LSTM) and a transfer learning strategy. The author introduced three transfer learning strategies with Stacked LSTM to reduce the forecast error and improve accuracy. In the first strategy, the author fixed the network layers' weight. In the second strategy, the author utilized data from the target domain and fine-tuned the network layers' weight. The author used the target domain data in the third strategy and trained the layers' weight. Finally, the stacked LSTM model with transfer learning of three strategies is compared against the Stacked LSTM without transfer learning. The results show the Stacked LSTM with transfer learning outgunned the Stacked LSTM without transfer learning by producing a 12.6% improvement in accuracy.

Goswami et al. (2022) introduced a short-term solar energy forecast model using a Bidirectional Gated Recurrent Unit (BGRU) with transfer learning. The transfer learning-based BGRU utilizes fewer parameters by 39.6% and reduces training time by 76.1% compared to the site-specific BGRU model. The output of the photo-voltaic cells in solar panels has a proportional relationship with GHI (Global Horizontal Irradiance). The author used solar irradiation data from 6 stations (Chennai, Howrah, Guntur, Kotada Pitha, Ajmer & Dehradun) to experiment with BGRU and T-BGRU. The results show the TGRU improved the solar energy forecast output with less training time than BGRU. Sheng et al. (2022) introduced a transfer support vector regressor (Tr-SVR) for solar energy forecasting, combining SVR and transfer learning concepts to improve the solar forecast result. It also reduces the negative knowledge transfer and long-term dependencies between source and target stations by introducing a novel weighting model. Solar irradiation, temperature, wind speed, and other photovoltaic energy forecast features from four datasets were utilized for the experimental purpose. The results show the Tr-SVR outperformed ANN, SVR, Gaussian Mixture Regression (GMR), and Extreme Learning Machine (ELM) models.

Table 4: Review of transfer learning in solar energy forecasting.

Sl. No.	Author	Dataset	Methodology	Remarks
1.	Sarmas et al. (2022)	Portuguese energy community - PV production data Copernicus Atmosphere Data Store - Weather data	Stacked LSTM with a transfer learning strategy	Transfer learning was utilized for weight initialization and feature extraction for the newly built solar plant. With the transfer learning strategy stacked, LSTM attained a better solar power forecast for the target plant with the scarcity of data.
2.	Manandhar et al. (2023)	ARM: Atmospheric Radiation Measurement dataset	AlexNet and ResNet-101	The deep learning-based Alexnet and ResNet-101 extracted the required knowledge, like convolution features, from Total Sky-Imager images. It reduced the time taken for training and the resources required for modeling.
3.	Goswami et al. (2022)	Solar irradiation data from 6 stations: Chennai, Howrah, Guntur, Kotada Pitha, Ajmer, and Dehradun	T-BGRU: Bidirectional Gated Recurrent Unit (BGRU) with transfer learning	T-BGRU achieved better solar energy forecasting and reduced training time of 76.1% compared to BGRU
4.	Sheng et al. (2022)	Dataset D1 & D2: Nanya Technologic University-Microgrid lab Dataset D3: Nanya Technologic University of JTC CleanTech One Dataset D4: Solar Radiation Research Laboratory	Transfer Support Vector Regression (Tr-SVR)	D2, D3, and D4 are utilized as source datasets. D1 is utilized as the target dataset. Tr-SVR utilizes a novel weighting model to block negative knowledge by combining the source & target datasets and only transfers the positive knowledge from the source to the target model. The model achieved better solar energy forecasts and reduced the forecast error.
5.	Luo et al. (2022)	Australia - PV plant installation parameters European Center for Medium-range Weather Forecasts - weather features	Constraint long short-term memory with parameter-based transfer learning	Transfer learning with C-LSTM improved the stability and accuracy of solar power forecast
6.	Miraftabzadeh et al. (2023)	Hourly recorded photovoltaic power output, humidity, and ambient temperature of two PV plants (located within 1.25km proximity)	Long short-term memory with transfer learning	LSTM with transferred knowledge achieved a better day ahead PV power prediction. Numerical results represent the importance of transfer learning for the newly installed PV power plants for stable functioning.

Luo et al. (2022) presented a power generation forecasting model for a newly constructed solar plant using transfer learning with deep learning-based constraint LSTM (C-LSTM). The PV plant installation parameters and weather features were utilized for the simulation. The LSTM model was designed to forecast solar power, extracting prior knowledge using the K-nearest neighbor. The parameter-transferring strategies of two categories were introduced to

Table 5: Performance Metrics for Energy Forecasting.

Sl.No	Performance Metrics	Formula
1.	Mean Absolute Error (Zor et al. 2017)	$\frac{1}{n}\sum_{t=1}^{n}\lvert y_t - f_t\rvert$
2.	Mean Square Error (Zor et al. 2017)	$\frac{1}{n}\sum_{t=1}^{n}(y_t - f_t)^2$
3.	Root Mean Square Error (Zor et al. 2017)	$\sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t - f_t)^2}$
4.	Percentage Error (Subbiah & Chinnappan 2020a)	$\left(\frac{y_t - f_t}{y_t}\right) * 100$
5.	Mean Percentage Error (Subbiah & Chinnappan 2020a)	$\frac{1}{n}\sum_{t=1}^{n}\left(\frac{y_t - f_t}{y_t}\right) * 100$
6.	Mean Absolute Percentage Error (Zor et al. 2017)	$\frac{1}{n}\sum_{t=1}^{n}\lvert PE\rvert$
7.	Normalized Root Mean Square Error (Luo et al. 2022)	$\frac{RMSE}{\sum_{t=1}^{n} y_t}$
8.	Weighted Mean Absolute Percentage Error (Miraftabzadeh et al. 2023)	$\frac{\sum_{t=1}^{n}\lvert f_t - y_t\rvert}{\sum_{t=1}^{n}\lvert y_t\rvert} \times 100\%$
9.	Coefficient of Determination R^2 (Sarmas et al. 2022)	$1 - \frac{\sum_{t=1}^{n}(y_t - f_t)^2}{\sum_{t=1}^{n}(y_t - \bar{y}\,)^2}$
10.	Mean Bias Error (MBE) (Sarmas et al. 2022)	$\frac{1}{N}\sum_{t=1}^{n}(y_t - f_t)$
11.	Forecast Skill Index (Sarmas et al. 2022)	$1 - \frac{RMSE_p}{RMSE_r}$
12.	Symmetric Mean Absolute Percentage Error (Subbiah & Chinnappan 2020a)	$\frac{abs(y_t - f_t)}{abs(y_t) + abs(f_t))}$

enhance Strategy 1, which transfers the network parameters of Layer 1 and Layer 2 to the target model and fine-tuning the layers in the target model. In the second strategy, the parameters of layer 1 and layer 2 are fixed. It fine-tunes the remaining layer parameters only in the target model. As a result, the C-LSTM with transfer learning produces a better forecast than the C-LSTM.

Miraftabzadeh et al. (2023) developed a day-ahead photovoltaic power forecasting model using LSTM and a transfer learning strategy. The PV power and weather features are utilized for forecasting the PV power using LSTM. The performance of the LSTM is improved by utilizing a transfer learning strategy. Manandhar et al. (2023) utilized the deep neural network-based AlexNet and ResNet-101 with pre-trained models for forecasting solar irradiance. The total sky imager images from the Atmospheric Radiation Measurement dataset were utilized for the model simulation. The result shows the AlexNet and ResNet-101 with transfer learning produced better solar irradiance forecasts and reduced training time and resource requirements.

PERFORMANCE MEASURES

A variety of performance measures are utilized for determining the performance of forecasting and proving the superiority of the developed model. It also helps to represent the significance of the specific strategy in achieving better forecast results. The commonly utilized performance metrics in energy forecasting in literature by many researchers are given in Table 5. Let 'n' represents the number of samples in the dataset, 't' represents the time period, 'y_t' represents the real observed energy, 'f_t' represents the forecast energy, 'p' represents the developed model, and 'r' represents the baseline persistence model.

CONCLUSION

The rapid growth of the population requires energy forecasting globally. The modernization, digitalization, automation, and electrification mandate the energy demand to be satisfied with supply in the future. Non-conventional clean and green renewable energy sources are the powerful energy sources identified by researchers and governments to meet the energy requirement, especially in urban areas, save people's lives, and protect the environment from pollution. However, the uncertain characteristics of the electricity load, wind speed, wind energy, and solar irradiation impose complications in achieving accurate energy forecasting. Researchers have reviewed energy forecasting for a long time to overcome the challenges, especially for applications with noisy and limited data. With the advent of transfer learning strategies, forecasting with noisy and insufficient data achieved better accuracy. This paper reviewed the role of transfer learning in load forecasting, wind speed forecasting, wind power forecasting, and solar power forecasting. Parameter-based transfer learning was utilized by many researchers in energy forecasting. Many researchers utilized correlation measures for identifying similar plants for transferring knowledge to the target plants. The exploration of the review shows that machine learning and deep learning models with transfer learning strategy greatly help to achieve better energy forecasting results.

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