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Research Article

A Hybrid CNN-LSTM Model for Predicting Energy Consumption and Production Across Multiple Energy Sources

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ABSTRACT

This study leverages a comprehensive dataset provided by Energy Exchange Istanbul (EXIST), a prominent authority in energy data, encompassing hourly energy consumption and production data across Turkey. To enhance the accuracy of energy consumption and production forecasting, a variety of machine learning and deep learning models were employed, including linear regression (LR), random forest (RF), support vector regression (SVR), convolutional neural networks (CNN), long short-term memory networks (LSTM), and the proposed hybrid CNN-LSTM model. The study reformulates the time series data into a regression problem by applying the sliding window technique. The experimental findings reveal that the hybrid CNN-LSTM model outperforms other models in forecasting total energy consumption as well as the production of natural gas, hydro dam, lignite, hydro river, wind, and fuel oil. The hybrid model achieved superior performance metrics, including the lowest root mean square error (RMSE) and mean absolute error (MAE) values, alongside the highest coefficient of determination (R^2) scores. The enhanced predictive capability of the proposed approach is attributed to the synergistic combination of CNN's strength in capturing local patterns and LSTM's proficiency in modeling long-term temporal dependencies. This study underscores the effectiveness of the hybrid CNN-LSTM model in accurately forecasting energy consumption and production, thereby contributing significantly to the efficient utilization of energy resources and supporting informed decision-making in energy management. Experiments showed that CNN-LSTM outperforms the compared models with above 0.999 R^2.

1. Introduction

Over the last few decades, there has been an unprecedented increase in electricity demand worldwide. The main reasons for this increase include rapid population growth, significant technological advances, and the proliferation of electronic devices that have become integral to modern life. As the world's population grows, energy consumption rises parallel, necessitating a reliable and abundant electricity supply. Technological advances lead to the emergence of new energy-intensive industries and processes, further increasing demand. In light of these complexities, effective power system planning and management has become

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more critical than ever to ensure that electricity systems remain reliable and manageable. Accurate energy demand forecasting is not just essential but urgent to avoid system overloads and blackouts, which can have serious economic and social consequences.

Achieving a balanced and efficient energy system requires developing and applying precise and accurate forecasting models for energy production and consumption [1, 2]. These models are vital tools that help energy providers predict future needs and adjust their operations accordingly. By accurately forecasting demand, energy companies can optimize production schedules, manage resources more effectively, and reduce operational costs.

Accurate forecasting of energy consumption also facilitates better allocation of energy resources, allowing providers to distribute energy where and when it is most needed. Furthermore, accurate forecasts provide a systematic roadmap for energy savings and energy infrastructure improvements [3]. The importance of forecasting energy demand and generation consumption is growing every day, mainly as the world tackles the challenges of climate change and sustainable development.

Accurate forecasts provide decision-makers in industry and governments with invaluable guidance and reference points on future directions and plans [4]. Based on these forecasts, policymakers design regulations and incentives that promote efficient energy use, support renewable energy adoption, and ensure energy security. Accurate forecasts inform industry investment decisions, operational strategies, and risk management practices.

Data-driven models have played an important role in accurately forecasting energy production and consumption. Traditional regression algorithms and time series analysis techniques were used for electricity forecasting. While these methods provide a basic understanding, they often lack the ability to capture the detailed patterns and complexities in energy data. Factors such as weather variations, consumer behavior, economic fluctuations, and technological changes introduce non-linearities and interactions that traditional models may not adequately address.

As a result, as global electricity demand continues to grow, the role of accurate energy forecasting models is becoming increasingly critical. Using advanced data-driven approaches enables us to improve the reliability and efficiency of power systems while supporting sustainable energy initiatives. Accurate forecasts provide valuable insights for strategic decision-making in the public and private sectors, facilitating the development of policies and practices that balance economic growth with environmental responsibility.

Today, machine learning and deep learning techniques have become essential tools for addressing the increasing volume and complexity of data [5]. In various sectors such as energy, healthcare, finance, transportation, and agriculture, these methods enable the extraction of meaningful insights from large datasets, leading to more accurate predictions and effective decision-making mechanisms. While machine learning excels in identifying patterns and performing classifications through data-driven algorithms, deep learning offers advanced solutions by capturing complex structures and modeling long-term dependencies. The widespread application of these techniques not only enhances operational efficiency but also facilitates the sustainable and efficient management of resources. Therefore, machine learning and deep learning stand out as cornerstone technologies in the ongoing digital transformation of our era.

2. Related Works

This section reviews some important studies on energy consumption and production. First of all, in [1], the authors emphasize that existing studies generally ignore user behavior in energy consumption forecasting and propose to develop a cooling energy consumption forecasting model that considers user behavior to overcome this deficiency. For this purpose, a new model was tested using four machine learning algorithms: artificial neural network (ANN), deep neural network (DNN), classification and regression tree (CART), and bagging tree. A simulation dataset consisting of 3 months of hourly data, including 5760 energy usage cases, was used, and coefficient of variation, mean square error (MSE) and R^2 metric were applied for performance evaluations. The results show that all algorithms achieve accurate prediction results when sufficient data is used.

Similarly, Dong et al. [6] presented an energy consumption forecasting model to solve this problem, noting that existing research does not consider building operating conditions over different periods. In the experiments, hourly collected meteorological data and energy consumption data of an office building are used. Using an ensemble learning method, the proposed model extracted energy consumption patterns and built an energy consumption model for each pattern. This model was compared with an ANN and support vector regression (SVR), and the results showed that it outperformed the other models in terms of MSE and coefficient of variation of mean square error (CVMSE).

Furthermore, Hora et al. [7] emphasized that energy consumption forecasting is a challenging problem, and its importance is increasing day by day. They pointed out the need for a reliable and accurate forecasting model. Accordingly, they introduced a new meta-heuristic-based LSTM network model for energy consumption prediction. Using two publicly available datasets, they compared their method with LR, CNN, SVR, LSTM, and bidirectional long-short-term memory (BiLSTM) algorithms. They used the metrics of mean absolute percentage error (MAPE), MAE, MSE for performance evaluation. The results showed that the proposed model provided lower error rates.

Conversely, Wang et al. [3] proposed a novel methodology for consumption forecasting based on a LSTM algorithm. The performance of the proposed model is compared with that of the autoregressive moving average model (ARMA), the autoregressive fractionally integrated moving average model (ARFIMA), and the back propagation NN algorithms. The metrics of mean squared error (MSE), MAE, and MAPE are used for the comparison. Experiments with a dataset collected from a real industrial system demonstrated that the proposed model outperformed the other models.

In addition, Nie et al. [8] proposed a new hybrid method for home energy consumption based on a gradient-boosting regression tree (GBRT) and an autoregressive fractionally integrated moving average model. The proposed model is compared with iterative NN, SVR, ARFIMA model with a GBRT, and an ARFIMA model with an iterative neural network. A simulation dataset generated using the Simulink program is used. The experimental results show that the proposed hybrid method offers lower error rates regarding mean absolute, percentage, and squared errors.

In [9], highlighting the importance of solar power generation forecasting, the authors introduce a hybrid model combining a CNN, LSTM and a transformer. In the experiments, a publicly available dataset called Fingrid is used. The metrics of MAE, MAPE and MSE were used for performance evaluation. The experiments show that the proposed model offers lower error rates than six other methods: AB-net, GRU-CNN, ARIMA, DeepAR, and Prophet.

In [10], it is stated that fossil fuel power plants are harmful to human life, and more environmentally friendly solutions should be used for energy production. In this context, the authors focused on wind power generation forecasting. They used Extreme Gradient Boosting (XGBoost), Bayesian optimized multilayer perceptron, GBRT, ensemble method (gradient boosting and XGBoost), CNN, and LSTM hybrid model. In the experiments, the metrics of MAE, MAPE, MSE, and MSE were applied, and the results showed that the Bayesian optimized multilayer perceptron offers minimum error rates with acceptable runtime.

Alaraj et al. [11] emphasized that electrical energy consumption is increasing daily and that using renewable energy sources has become mandatory to meet the required consumption. This has made it even more important to predict the energy production of solar photovoltaic power plants. Therefore, the authors proposed a model based on the community tree approach and performed experimental studies on a collected dataset. The metrics of MSE, MAE, MAPE are used as performance indicators, and the results show that the proposed model offers lower error rates.

Similarly, in reference [12], the authors concentrated on a comparative analysis of the performance of machine learning algorithms for solar power generation forecasting. A variety of algorithms were employed, including SVM, k-nearest neighbor, random forest, artificial neural networks, naive Bayes, logistic regression, decision tree, gradient boosting, adaptive boosting and stochastic gradient descent. The experiments were conducted using a collected dataset, with the area under the curve and MAPE applied as performance metrics. The results demonstrated that SVM yielded the most optimal outcomes.

Finally, Ledmaoui et al. [13] presented a comparative study for solar power generation forecasting. In this study, Extreme Gradient Boosting (XGBoost), Gradient Boosting Machine (GBM), recurrent neural network (RNN), and ANN are compared. A collected dataset was used for the experiments, and MSE, MAE, and R^2 metric were applied for performance evaluation. As a result, it is observed that ANN gives the best prediction results compared to other methods.

Overall, these studies demonstrate the effectiveness of different approaches and models in energy consumption and production forecasting. Machine learning and artificial intelligence-based methods seem to provide higher accuracy and efficiency in energy forecasting. Therefore, developing these methods further and applying them to different energy sources in future research will be important.

3. Material and Methods

3.1 Dataset

This study used a dataset consisting of energy consumption and production values provided by Energy Exchange Istanbul (EXIST). The dataset used publicly available via [14]. The dataset includes hourly energy consumption and production values in Megawatts between 01/01/2018 and 31/12/2023 throughout Turkey. The dataset used consists of the attributes time, total production and consumption, natural gas, hydro dam, lignite, hydro river, coal imported, wind, solar, fuel oil, geothermal, asphalted coal, hard coal, biomass, naphtha, LNG, international, waste heat, TRY/MWh, USD/MWh and EUR/MWh. This study selected the attributes of total consumption amount and natural gas, hydro dam, lignite, hydro river, wind, and fuel oil production amounts. Figure 1 shows the change graphs of the values of the selected attributes over time.

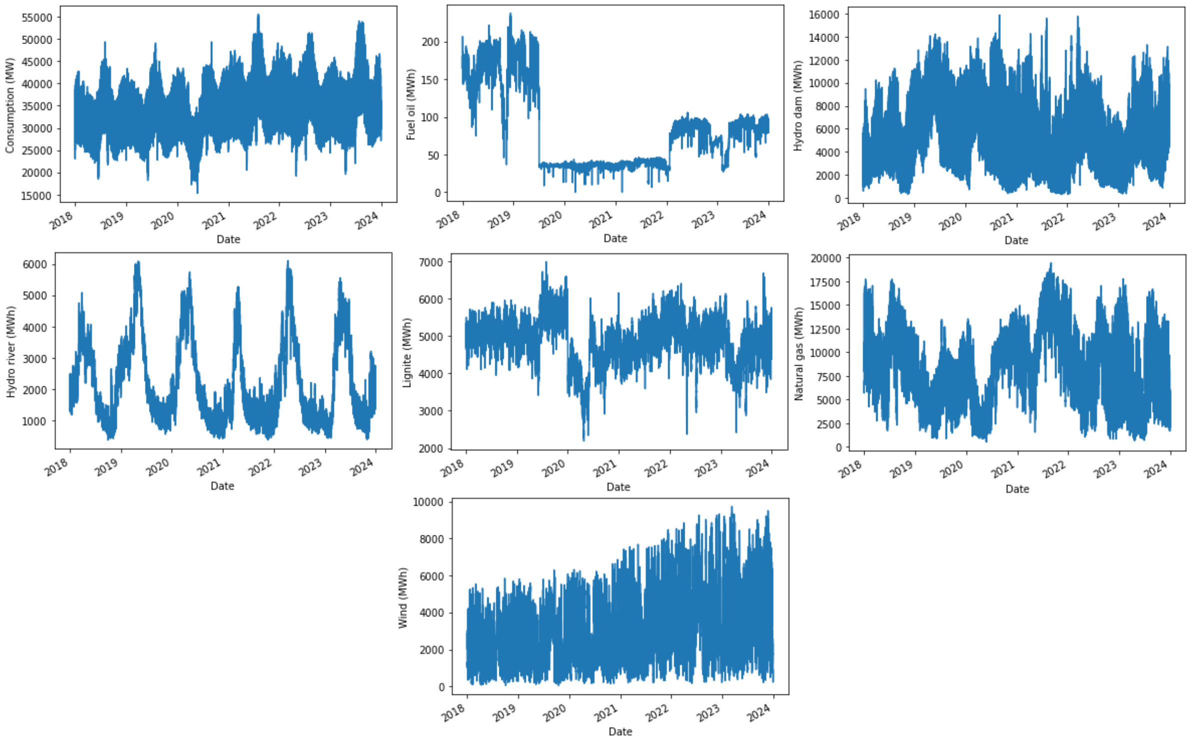

Figure 1. The change graphs of the values of the selected attributes over time

In Figure 1, sharp increases and decreases in consumption or production are observed according to seasons and periods, economic changes, and energy demand. The change in total production and total consumption over time is shown in Figure 2.

Figure 2 shows the change in total energy production and total consumption over time. Consumption and production values are generally close to each other, but in some periods, production is greater than consumption. The change in total consumption by month is shown in Figure 3.

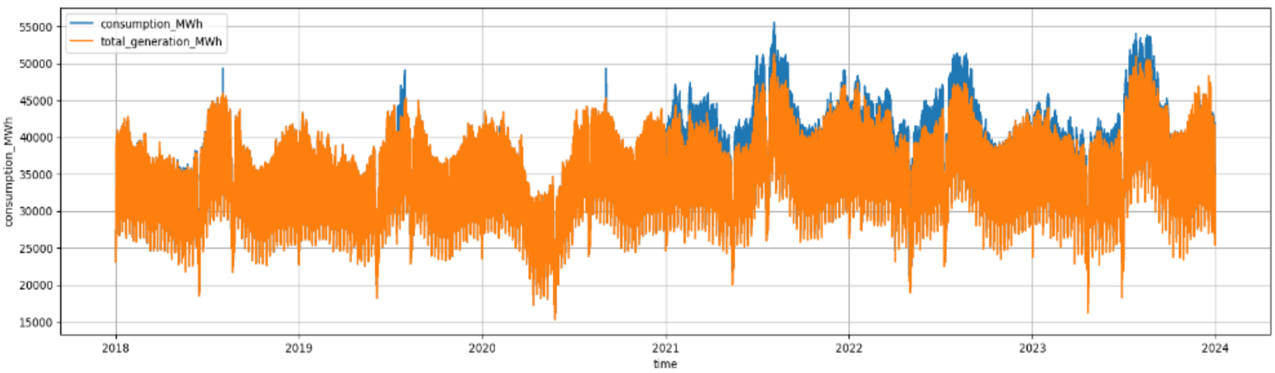

Figure 2. The change in total production and total consumption over time

Figure 3 shows the change in energy consumption by month. While the lowest energy consumption is observed in April, the highest energy consumption is observed in August. There are differences between the other months according to seasonal changes.

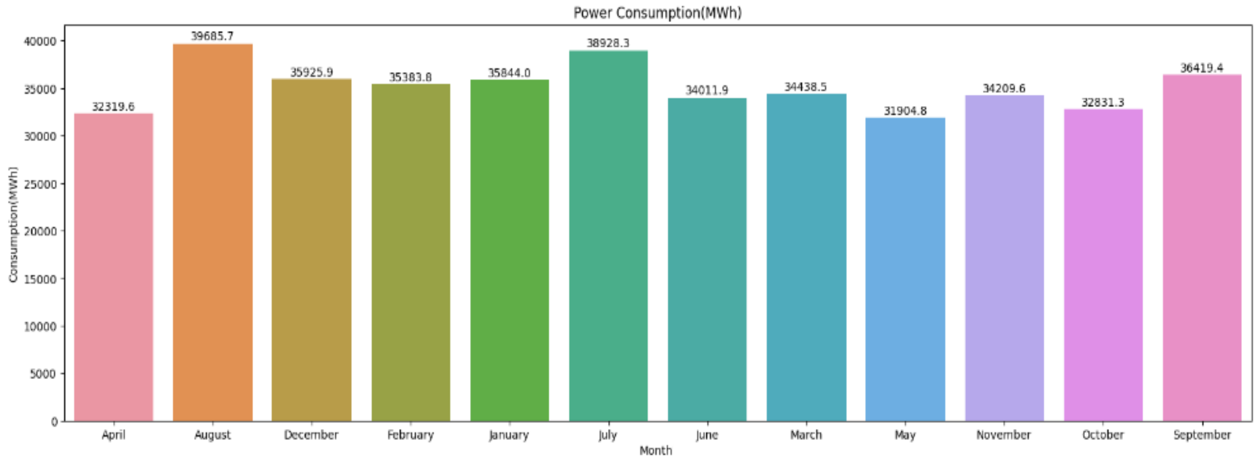

Figure 3. The change in total consumption by months

3.2 Prediction Models

In this study, a dataset provided by Energy Exchange Istanbul (EXIST) was utilized, containing hourly energy consumption and production values across Turkey between January 1, 2018, and December 31, 2023. To predict energy consumption and production more accurately and reliably across different energy sources, various machine learning and deep learning methods were employed, including LR, RF, SVR, CNN, and LSTM. Linear regression was chosen for its simplicity and interpretability, while methods like random forest and SVR excel in capturing complex data relationships. Deep learning models such as CNN and LSTM are particularly effective in learning hidden patterns and temporal dependencies in time-series data. The selected features from the dataset include time, total consumption amount, and production amounts of natural gas, hydro dam, lignite, hydro river, wind, and fuel oil. This comprehensive approach aims to achieve more precise predictions of energy consumption and production, thereby promoting more efficient use of energy resources.

The technique of linear regression [15] represents a fundamental statistical methodology which models the linear relationship between a dependent variable and one or more independent variables. This is achieved by fitting a linear equation to observed data. The simplicity and interpretability of linear regression make it an advantageous technique for regression tasks, allowing for quick implementation and computational efficiency. As a robust baseline model for predictive analysis, linear regression provides clear insights into how each predictor affects the outcome, thus helping to identify critical factors influencing energy consumption and production. Furthermore, its transparent nature makes it valuable for understanding the direct impact of individual energy sources on overall energy metrics [16].

Random Forest [17] is an ensemble learning method that constructs multiple decision trees with randomness in the tree-building process—selecting random subsets of features and samples—to reduce overfitting and improve model generalization by averaging their predictions. This approach enhances robustness to noise and outliers, captures complex nonlinear relationships without extensive parameter tuning, and effectively handles large, high-dimensional datasets by modeling interactions between variables. In the context of energy forecasting, Random Forest discerns intricate patterns in consumption and production data across different energy sources, leading to more accurate and reliable predictions [18, 19].

Support Vector Machines [20] are supervised learning models that are employed for the purposes of classification and regression.; in regression tasks, known as SVR [21], they aim to find a function that deviates from the observed values by no more than a specified margin, employing kernel functions to transform input data into a higher-dimensional space where a linear relationship can be established. SVRs offer a number of advantages in modelling non-linear relationships using a variety of kernel functions. They are particularly effective in high-dimensional spaces and demonstrate resilience to overfitting, especially when the number of dimensions exceeds the number of samples. In energy consumption and production prediction, SVRs can capture subtle and complex dependencies between different energy sources and consumption patterns [22].

CNNs are deep learning models that process grid-like data by learning spatial hierarchies of features through convolutional layers and backpropagation, utilizing components like convolution, pooling, and fully connected layers [23]. Adapted for regression tasks with time-series data, CNNs capture local patterns and trends by treating temporal data similarly to spatial data, requiring fewer parameters than fully connected networks and reducing the risk of overfitting [24]. In energy forecasting, CNNs effectively learn temporal and spatial correlations in consumption and production data across different energy sources, enhancing the accuracy of predictions [25].

Long Short-Term Memory (LSTM) networks represent a specific type of recurrent neural network, designed for the purpose of modelling sequential data. This is achieved through the utilisation of memory cells, which maintain information over extended periods, effectively addressing the vanishing gradient problem that is inherent to traditional RNNs. Particularly beneficial for time-series forecasting in regression tasks, LSTMs excel at learning temporal patterns and trends from historical data [26-28]. In the context of energy consumption and production prediction, they can model the dynamic behavior of energy systems by capturing seasonal variations and temporal dependencies, handling sequences of varying lengths, and focusing on relevant time steps, making them highly effective for accurate and reliable energy forecasting [29].

3.3 Created Hybrid Prediction Model

In this study, a time series dataset of hourly energy consumption and production amounts was used. To process time series data with machine learning or deep learning, datasets must be transformed into regression problems. The sliding window method is used to transform time series data into a regression problem structure. The sliding window method allows the data to be structured as input/output according to the specified window size, as seen in Figure 4. As seen in Figure 1, in a scenario where the window size is 3, t_1, t_2 and, t_3 will be configured as input, and t_4 will be configured as output. The sliding window progresses by shifting one observation data to the right at each step.

A series of experimental studies were conducted with the objective of determining the optimal sliding window size. The models had the lowest error rate when the sliding window size was 3. The data was input/output structured using sliding windows and scaled using MinMaxScaler.

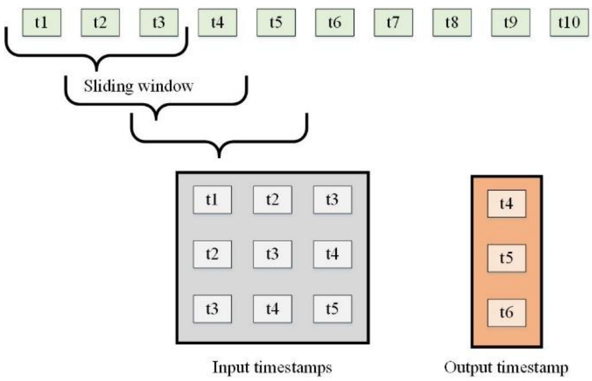

Figure 4. Sliding window method

80% of the data set was used for model training and 10% of the training data was used as validation data for model hyper-parameter determination. The models were tested on 20% of the dataset. Grid search was used to determine the hyper-parameters of the models. Grid Search is a common method used to perform hyper-parameter optimization in machine learning and deep learning models. In this process, all possible combinations for a given set of hyper-parameters are tested and the performance of the model is evaluated.

The hyper-parameter combination that provides the best performance is selected. The structure of the created CNN-LSTM model is presented in Figure 5.

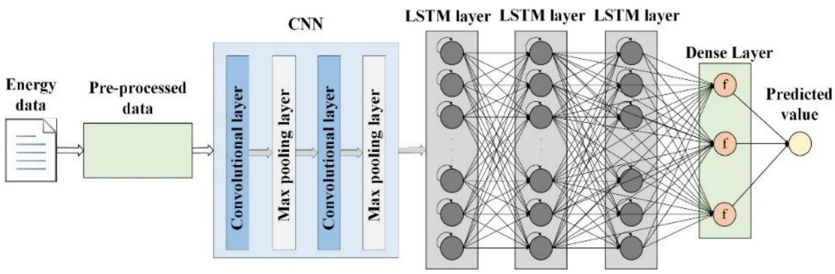

Figure 5. The structure of the created CNN-LSTM model

As seen in Figure 5, the created CNN-LSTM model consists of CNN and LSTM components. CNN was used for feature extraction and determining patterns between data. LSTM was used to learn long and short term dependencies between data. The created CNN-LSTM model takes hourly energy production and consumption values as input. The data is presented as input to CNN after being pre-processed using sliding window and MinMax scaler. CNN component uses convolution and pooling layers to extract features and determine patterns between data. LSTM component processes the feature maps provided by CNN component and enables modeling the relationships between data and learning long-short term dependencies. For the CNN component determined using grid search, the number of convolution and pooling layers is 2; the activation function is ReLU, the pool size is 2 and the number of filters is 32. LSTM component has 32 neurons and Adam optimizer is used. Dropout rate is 0.2, epoch is 80 and batch size is 8.

Hyper-parameters for LR are fit_intercept: True and normalize: False. Hyper-parameters for RF are 100, n_estimators: 100, max_depth: 20, min_samples_split: 2, min_samples_leaf: 1, and max_features: 'auto'. Hyper-parameters for SVR are C:10, kernel: linear, gamma=1e-07, and epsilon=0.1. Hyper-parameters for CNN: number of filters: 64, kernel_size: (3, 3), pool_size: (2, 2), activation function: relu, optimizer: adam, batch_size: 64, and epochs: 100. Hyper-parameters for LSTM: number of neurons: 100, dropout: 0.2, recurrent_dropout: 0.2, batch_size: 64, learning_rate: 0.001, optimizer: adam, and epochs: 100.

4. Experimental Results

In this study, a hybrid CNN-LSTM model was created for the prediction of total consumed energy and production of natural gas, hydro dam, lignite, hydro river, wind, and fuel oil. The created model was comprehensively compared with LR, RF, SVR, CNN and LSTM. Table 1 shows the experimental results for predicting total energy consumption.

Table 1. The experimental results for predicting total energy consumption

Model	RMSE	MAE	R^2
LR	1086.87	761.63	0.964
RF	1073.88	755.95	0.965
SVR	1034.90	747.93	0.968
CNN	927.85	639.22	0.974
LSTM	834.40	597.13	0.981
CNN-LSTM	741.27	541.07	0.990

In Table 1, it is observed that all models are generally successful in predicting total energy consumption. The compared models had R^2 values above 0.9. CNN-LSTM was more successful than the compared models with the lowest MAE and RMSE and the highest R^2. Table 2 presents the experimental results for predicting natural gas production.

Table 2. The experimental results for predicting natural gas production

Model	RMSE	MAE	R^2
LR	740.01	513.13	0.965
RF	732.59	501.57	0.965
SVR	731.35	498.86	0.966
CNN	729.71	498.23	0.966
LSTM	686.92	431.74	0.972
CNN-LSTM	524.48	357.27	0.984

Table 2 shows that LSTM and CNN-LSTM are more successful than other models. LR, RF, SVR and CNN had close results. CNN-LSTM was more successful than the models compared with an R2 of 0.984. Table 3 presents the experimental results for predicting fuel oil production.

Table 3. The experimental results for predicting fuel oil production

Model	RMSE	MAE	R^2
LR	3.07	1.66	0.969
RF	3.00	1.58	0.971
SVR	2.99	1.52	0.971
CNN	2.86	1.36	0.973
LSTM	2.75	1.09	0.980
CNN-LSTM	1.13	0.63	9.992

Table 3 shows that LR, RF, SVR and CNN have close results. CNN-LSTM outperformed the compared models with 1.13 RMSE, 0.63 MAE, and 0.992 R^2. Table 4 presents the experimental results for predicting hydro river production.

Table 4. The experimental results for predicting hydro river production

Model	RMSE	MAE	R^2
LR	111.86	86.32	0.989
RF	109.73	83.85	0.993
SVR	105.30	79.76	0.993
CNN	105.13	79.60	0.993
LSTM	101.84	74.47	0.995
CNN-LSTM	92.04	61.79	0.998

As seen in Table 4, all models except LR had R2 above 0.9. CNN-LSTM outperformed the compared models with 92.04 RMSE, 61.79 MAE, and 0.998 R^2. Table 5 presents the experimental results for predicting hydro dam production.

Table 5. The experimental results for predicting hydro dam production

Model	RMSE	MAE	R^2
LR	698.38	535.45	0.908
RF	647.10	497.02	0.921
SVR	632.55	484.06	0.925
CNN	622.91	483.62	0.927
LSTM	573.80	419.22	0.943
CNN-LSTM	489.93	333.07	0.961

As seen in Table 5, LR is relatively less successful than other models. SVR and CNN gave similar results and were more successful than RF. LSTM was successful after CNN-LSTM with 0.943 R^2. CNN-LSTM was the most successful model with 0.961 R^2. Table 6 presents the experimental results for predicting hydro dam production.

Table 6. The experimental results for predicting lignite production

Model	RMSE	MAE	R^2
LR	178.74	88.14	0.899
RF	172.61	86.20	0.905
SVR	172.47	85.21	0.906
CNN	164.54	80.11	0.915
LSTM	143.25	69.84	0.934
CNN-LSTM	117.21	48.44	0.957

As seen in Table 6, all models except LR had R^2 above 0.9. RF and SVR gave close results. CNN-LSTM was the most successful model with R^2 of 0.957. Table 7 presents the experimental results for predicting wind power production.

Table 7. The experimental results for predicting wind power production

Model	RMSE	MAE	R^2
LR	181.12	135.77	0.990
RF	175.54	131.45	0.992
SVR	171.36	127.63	0.993
CNN	169.22	125.78	0.993
LSTM	157.56	115.87	0.995
CNN-LSTM	127.23	96.42	0.999

As seen in Table 7, all models had R^2 above 0.9. RF, SVR and CNN had similar results. LSTM had R^2 of 0.995 and CNN-LSTM had 0.999 R^2.

Figure 6 shows the comparative experimental results with respect to RMSE and MAE for energy production and consumption.

Figure 7 shows the comparative experimental results for energy production and consumption with respect to R^2.

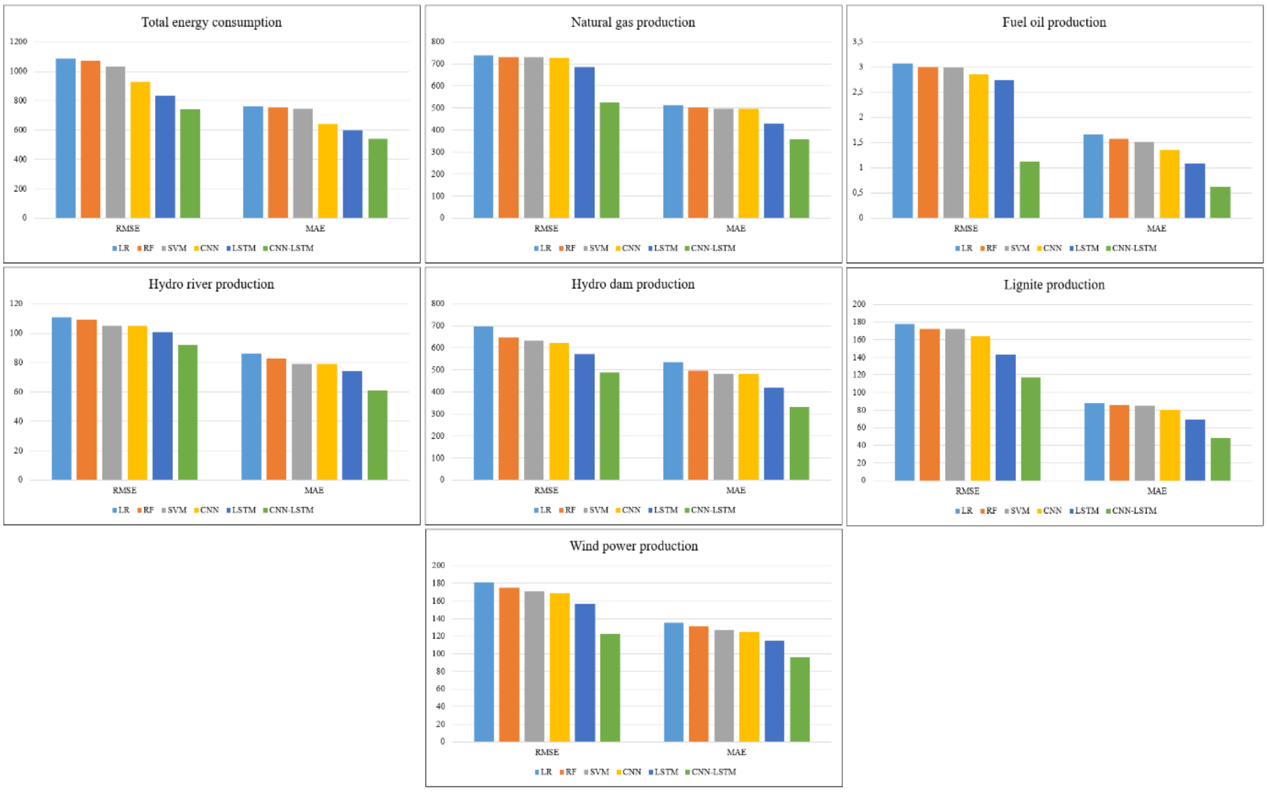

Figure 6. The comparative experimental results with respect to RMSE and MAE for energy production and consumption

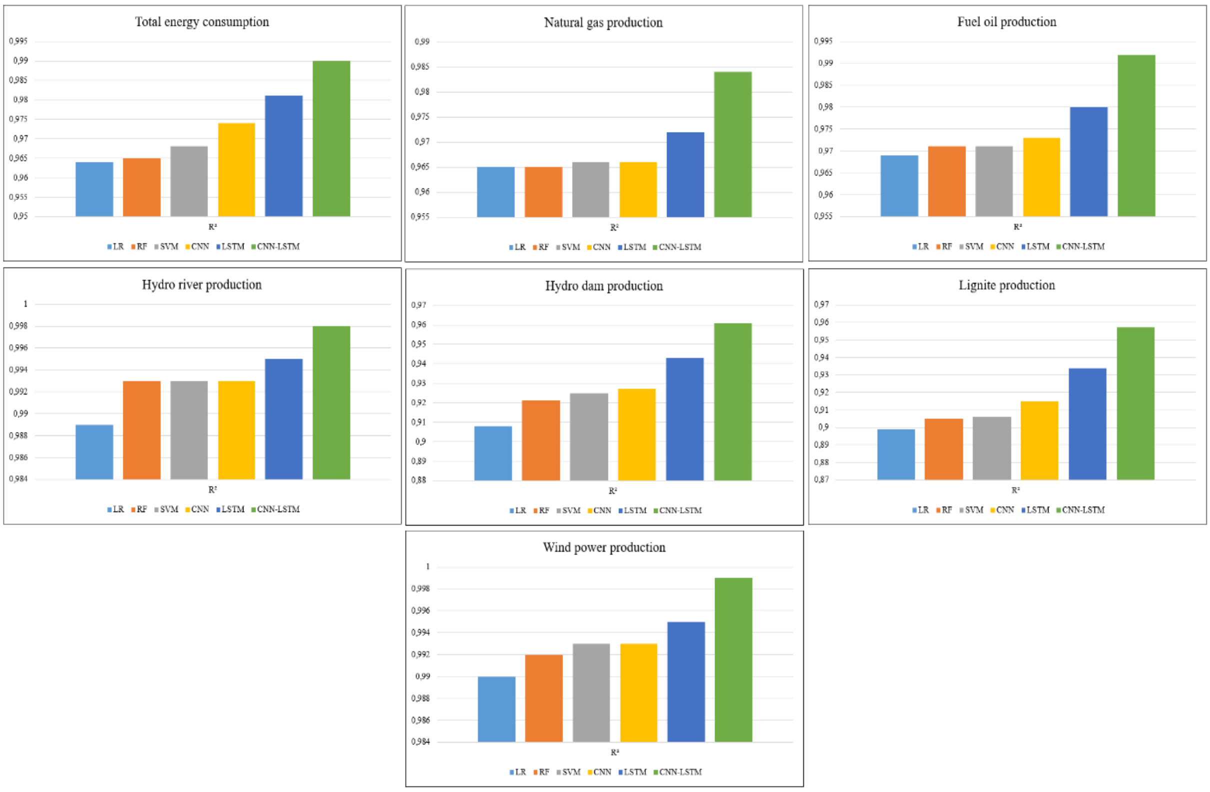

Figure 7. The comparative experimental results for energy production and consumption with respect to R^2

Experiments showed that CNN-LSTM outperformed the compared models for total energy consumption and production of natural gas, hydro dam, lignite, hydro river, wind and fuel oil, as seen in Figure 6 and Figure 7. CNN-LSTM was more successful than the compared models because CNN-LSTM enables the determination of spatial and temporal relationships thanks to its hybrid structure. CNN extracted local patterns in energy production and consumption data, while LSTM enabled the learning of short-term trends and long-term dependencies.

The success of LSTM can be explained by its capacity to capture long-term dependencies in time series data. Since the dataset used is dependent on external factors such as seasonal changes and energy demand, LSTM was able to successfully model the dependencies in the dataset. CNN is an effective model in capturing short-term patterns, but CNN's ability to capture long-term dependencies is limited. CNN was inefficient compared to CNN-LSTM and LSTM because it could not capture long-term relationships. SVR, RF and LR are not efficient enough in datasets such as complex and nonlinear time series. Especially in time series data, since the observation data are dependent on each other, traditional machine learning methods cannot capture long-term and short-term dependencies.

5. Conclusion

The objective of this study was to evaluate the efficacy of diverse machine learning and deep learning methodologies for energy forecasting, utilising hourly energy consumption and production data from across Turkey. Comprehensive experiments were conducted on LR, RF, SVR, CNN, LSTM, and the proposed hybrid CNN-LSTM model. Time series data were transformed into a regression problem using the sliding window method, allowing the models to learn temporal dependencies.

The findings of the experimental study indicated that the hybrid CNN with LSTM model exhibited superior performance in predicting total energy consumption and the production quantities of diverse energy sources in comparison to other models.

In particular, the CNN-LSTM model achieved the lowest error rates according to RMSE, MAE and the highest coefficient of determination according to R^2. This success is attributed to the combination of CNN's ability to identify local patterns and LSTM's capability to capture long-term dependencies in the data.

The findings highlight the effectiveness of deep learning-based hybrid models in energy forecasting. They significantly contribute to more accurate predictions of energy production and consumption, enabling more efficient use of energy resources and the development of improved energy management strategies.

Future studies can explore the model's generalizability to different energy markets and regions. Incorporating additional factors such as seasonal changes, economic indicators, and weather conditions into the model could enhance prediction accuracy. Moreover, applications like real-time forecasting and integration with smart energy management systems can be considered for practical implementations

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