REPUBLIC OF TÜRKİYE
ADANA ALPARSLAN TÜRKEŞ SCIENCE AND TECHNOLOGY UNIVERSITY

GRADUATE SCHOOL
ELECTRICAL AND ELECTRONIC ENGINEERING DEPARTMENT

THE SECTORAL ELECTRICITY LOAD FORECASTING BY USING DEEP LEARNING TECHNIQUES

ABDURRAHMAN YAVUZDEĞER

Ph.D.

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ADANA, 2024

DECLARATION OF CONFORMITY

In this thesis study, which was prepared following the thesis writing rules of Adana Alparslan Türkeş Science and Technology University Institute of Graduate School, I declare that I provide all the information, documents, evaluations and results in accordance with scientific ethics and moral codes without resorting to any means or assistance that would be contrary to scientific ethics and traditions. I also declare that I refer to all of the articles I used in this study with appropriate references and accept all moral and legal consequences if a situation is found contrary to my statement regarding my work.

25/06/2024

[Signature]

Abdurrahman YAVUZDEĞER

ÖZET

DERİN ÖĞRENME TEKNİKLERİ KULLANILARAK SEKTÖREL ELEKTRİK YÜK TAHMİNİ

Abdurrahman YAVUZDEĞER
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II. Danışman: Dr. Öğr. Üyesi İnayet Özge AKSU

Haziran 2024, 126 sayfa

Elektrik yükünün tahmin edilmesi, küresel enerji talebinin artması ve enerjinin şebekelerde etkin yönetimine duyulan ihtiyaç nedeniyle kritik bir konudur. Bu çalışma, elektrik yükünü tahmin etmek için Uzun Kısa Süreli Bellek (UKSB), Evrişimsel Sinir Ağı (ESA) ve hibrit bir ESA-UKSB modelini içeren Derin Öğrenme (DÖ) modellerini kullanmayı amaçlamaktadır. 2016-2023 yılları arasındaki aylık veriler kullanılarak, aydınlatma, konut, sanayi, tarım, ticari ve toplam yük referans alınarak, Adana, Mersin ve Antalya illerinde farklı sektörlerdeki elektrik yükü tahmin edilmektedir. Matlab/Simulink modeli 24 saatlik elektriksel yük profilini gözlemlemek için kullanılmıştır. Tezin ana katkısı, DÖ yaklaşımlarının ve hibrit uygulamalarının karşılaştırmalı bir analizinin incelenmesi ve önerilmesidir. Karşılaştırma sonuçları, DÖ modellerinin stratejik enerji planlamasındaki önemine odaklanan karmaşık kalıpları yakalamada DÖ modellerinin etkinliği açısından dikkate değer bilgiler ortaya koymaktadır. Ortalama Karekök Hata (OKH), R^2, Ortalama Mutlak Yüzde Hata (OMYH) ve Ortalama Mutlak Hata (OMH) açısından hibrit modellerin UKSB ve ESA modeline üstünlük sağladığı sonucuna varılmıştır. Sonuçlar, ESA-UKSB hibrit modellerinin sektörel elektrik yüklerinin zamansal dinamiklerini yakalama yeteneğinin, UKSB ve ESA'dan daha etkili olduğunu göstermektedir.

Anahtar Kelimeler: evrişimsel sinir ağı, derin öğrenme çerçevesi, elektrik yükü tahmini, uzun kısa süreli bellek

ABSTRACT

THE SECTORAL ELECTRICITY LOAD FORECASTING BY USING DEEP LEARNING TECHNIQUES

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June 2024, 126 pages

Forecasting of electricity load is a critical issue because of the increasing global demands for energy and the need for its efficient management in grids. This study aims to utilize Deep Learning (DL) models, including Long Short-Term Memory (LSTM), Convolutional Neural Network (CNN), and a hybrid CNN-LSTM model, for forecasting electricity load. Monthly data from 2016 to 2023 is used to predict the electricity load in the provinces of Adana, Mersin, and Antalya in different sectors, concerning lighting, residential, industry, agriculture, commercial, and total load. The Matlab/Simulink model has been used to observe the 24-hour electrical load profile. The main contribution of the thesis is to examine and propose a comparative analysis of DL approaches and their hybrid applications. Comparison results illustrated noteworthy information in terms of the effectiveness of DL models in capturing complex patterns, which focused on the importance of DL models in strategic energy planning. It was concluded that concerning Root Mean Square Error (RMSE), R^2, Mean Absolute Percentage Error (MAPE), and Mean Absolute Error (MAE), the hybrid model provides superiority to the LSTM and CNN models. The results show that the capability of CNN-LSTM hybrid models in capturing the temporal dynamics of sectoral electricity loads is more effective than the LSTM and CNN as the case.

Keywords: convolutional neural network, deep learning framework, electricity load forecast, long short-term memory

Dedication

to My Beloved Family: Harika & Atlas

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In the preparation of this thesis, I would like to thank my advisor Assoc. Prof. Dr. Tuğçe DEMİRDELEN has always been exemplary in her knowledge, business approach, skills, and broad perspective.

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LIST OF ABBREVIATIONS

ELF	: Electricity Load Forecasting
VSTLF	: Very Short-Term Load Forecasting
STLF	: Short-Term Load Forecasting
MTLF	: Medium-Term Load Forecasting
LTLF	: Long-Term Load Forecasting
ML	: Machine Learning
DL	: Deep learning
CNN	: Convolutional Neural Network
LSTM	: Long Short-Term Memory
DLSTM	: Deep Long Short-Term Memory
BiLSTM	: Bidirectional Long Short-Term Memory
RNN	: Recurrent Neural Network
GRU	: Gated Recurrent Unit
DBN	: Deep Belief Network
BRNN	: Bidirectional Recurrent Neural Network
TCN	: Temporal Convolutional Network
WNN	: Wavelet Neural Network
EMD	: Empirical Mode Decomposition
SVR	: Support Vector Regression
RF	: Random Forest
ELM	: Extreme Learning Machine
GAN	: Generative Adversarial Network
ESN	: Echo State Network
NRE	: Nonlinear Relationship Extraction
FFNN	: Feed Forward Neural Network
MAPE	: Mean Absolute Percentage Error
GRU	: Genetic Algorithm
SVM	: Support Vector Machine
PSO	: Particle Swarm Optimization
MAE	: Mean Absolute Error

ARIMA	: Autoregressive Integrated Moving Average
SARIMAX	: Seasonal Autoregressive Integrated Moving Average with Exogenous
ANN	: Artificial Neural Network
PV	: Photovoltaic
EMRA	: Energy Market Regulatory Authority
ReLU	: Rectified Linear Unit
ANFIS	: Adaptive Neuro-Fuzzy Inference System
RMSE	: Root Mean Square Error
TFT	: Temporal Fusion Transformer
RR	: Ridge Regression

1. INTRODUCTION

1.1. Overview of Electricity Load Forecasting

Electricity load forecasting (ELF) is a vital aspect of managing power systems, involving the prediction of future electricity demand to maintain grid stability, ensure efficient energy distribution, and guide infrastructure development (Baur et. al., 2024; Gu et. al., 2024). This practice spans predicting electricity usage from a few minutes to several years into the future. The precision of these forecasts is crucial for energy producers, grid operators, and financial analysts, influencing decisions related to generation scheduling, load switching, maintenance planning, and energy trading (Bin Kamilin and Yamaguchi, 2024).

Effective load forecasting allows utility companies and government agencies to make proactive decisions about energy production and investment strategies. With the growing complexity of electricity networks and the rising incorporation of renewable energy sources, the accuracy of load forecasts has become increasingly essential. Accurate load forecasts enable utility companies to manage their resources more efficiently, minimizing operational costs by optimizing generation and reducing waste. These forecasts also support long-term planning and investment decisions in infrastructure, ensuring the grid remains reliable and capable of meeting future demands (Jin et. al, 2024).

In energy markets, load forecasting influences pricing mechanisms (Ghimire et. al., 2024; Monjazeb et. al., 2024; Nie et. al., 2024). Accurate forecasts contribute to setting competitive and fair prices. Additionally, with the increasing integration of renewable energy sources, which are often intermittent, load forecasting becomes even more critical to dynamically balance supply and demand. Forecasting electricity demand involves several techniques and methodologies, ranging from simple statistical methods to complex Machine Learning (ML) models (Eren and Küçükdemiral, 2024). The choice of method depends on various factors, including the time horizon of the forecast, the availability of historical data, and the specific requirements of the application. ELF process in the power grid is presented in Figure 1.1.

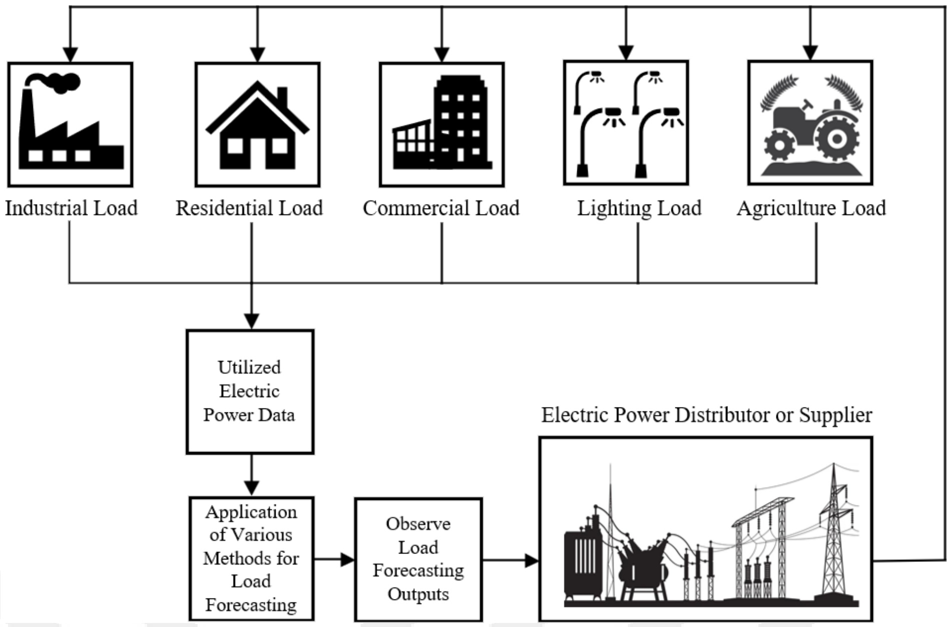


Figure 1.1. ELF process in the power grid.

Load forecasting is further complicated by the integration of renewable energy sources, such as solar and wind, which are intermittent and variable in nature (Kaur et. al., 2016; Aslam Sheraz et. al., 2021; Randall et. al., 2023). The forecasting of renewable energy generation needs to be accurate for balancing supply and demand to ensure grid stability. The utility companies also rely on load forecasts to optimize their generation schedules to produce enough electricity to meet the demand without, at the same time, leading to overproduction. So, operational costs are kept at a bare minimum, and the system runs at maximum efficiency. The load factor of electricity in a region is highly varied by political, economic, social, and technological factors, as indicated in Figure 1.2. The Political factors include government interventions like incentive policies that increase electricity consumption and repressive policies like power cut-off measures in cases of coal shortages that may reduce it. Economic factors prove a strong correlation between growth and electricity demand. For example, the global economic downturn due to the pandemic has now resulted in a decline in electricity consumption. Social factors will also focus on the population size and activities on electricity demand. As the population grows at a high rate, there will be high electricity consumption. In contrast, the increasing standard of living among people and being conscious of green consumption practices lead to and contribute to energy-saving practices. Behavioral practices of recycling and reusing devices will not need much electricity. Climate change also has a significant effect on residential electricity demand. Technological factors will focus on innovation and energy consumption. This includes techniques like ultra-high-voltage power grid technology, which furthers the possible transmission of power over long distances and thus increases the supply of renewable energy. Groundbreaking in technology, such as decarbonization in the power industry using carbon capture and storage, is indispensable for raising the proportion of renewable energy generation and promoting development in the industry.

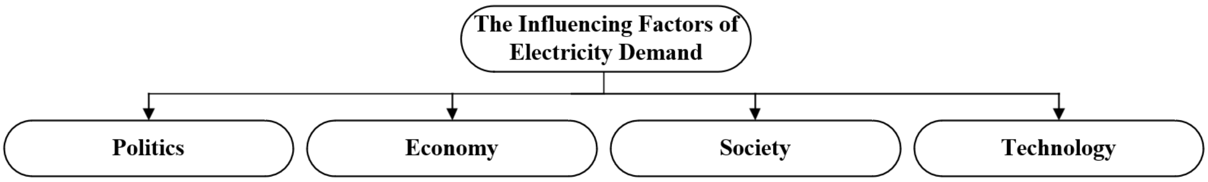


Figure 1.2. Factors affecting electricity demand.

Accurate load forecasting also holds the key to a reduction of environmental impact with electricity generation. In this way, utility companies reduce their generation of greenhouse gases by utilizing renewable sources in the best way possible and minimizing the utilization of fossil fuels, thus contributing positively to a more sustainable energy future. Accurate load forecasting techniques in energy markets facilitate better strategies for electricity pricing, hence competitive, justifiable, and fair pricing of electricity. This can be achieved at a relatively lower price to the consumers and with greater market operation efficiency. Moreover, the provision of power system stability and reliability also largely depends on the correct load forecast. The grid operator can perform some actions before the forecasted high-demand periods in such a manner as to prevent blackouts and to keep on supplying electricity to the consumers. It is essential, in power systems management, to take care of the ELF. Its relevance is beyond that of operational efficiency alone. It extends to areas that appear to be distant, for example, long-term planning, investment decisions, pricing mechanisms, and the integration of renewable energy sources. The growing complexity of electricity networks and increased demand for sustainable energy solutions require higher system operation efficiency with loads of forecast accuracy and reliability to ensure a secure and efficient power supply.

1.2. Classification of Load Forecasting

Load forecasting is divided into four categories: Very Short-Term Load Forecasting (VSTLF), Short-Term Load Forecasting (STLF), Medium-Term Load Forecasting (MTLF), and Long-Term Load Forecasting (LTLF) as shown in Figure 1.3 (Azeem et. al., 2021).

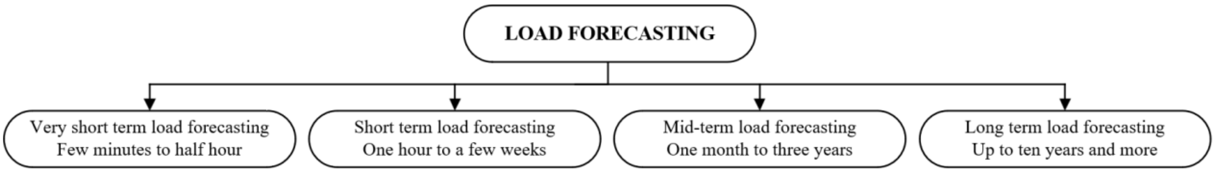


Figure 1.3. Classification of load forecasting.

Effective energy management depends on providing accurate forecasting over a range of different time horizons. VSTLF provides critical support to energy purchasing, demand-side management, and very immediate operational tasks (Junior et. al., 2024; Charytoniuk and Chen, 2000). STLF is essential for operational and tactical daily planning in performing the complex and challenging task of balancing supply against demand (Hippert et. al., 2001; Kwon et. al., 2020). This type of forecasting is done as an alternative to scheduling generation and dispatching loads daily. Among the techniques used in STLF are the statistical ones, which involve time series analysis and regression models; ML approaches use neural networks and SVMs (Li et. al., 2020; Guo et. al., 2021; Eskandari et. al. 2021). All these methodologies base their predictions on historical load data, weather conditions, and calendar information to predict accurate outputs.

MTLF is usually one month to three years and, therefore, helps in planning both the time for carrying out the maintenance activities and in preparing the finances required (Ghiassi et. al., 2006; Shirzadi et. al., 2021; Matrenin et. al., 2022; Wang et. al., 2019). This makes it an essential tool in planning, budgeting, and allocating resources for the system (Feilat et. al, 2011). Techniques used to compute the MTLF are generally a blend of statistical methods with simulation models. The more common ones use regression analysis and exponential smoothing and, from time to time, scenario analysis, mainly to reflect the effects of uncertain economic conditions and policy changes (Dudek et. al., 2021).

LTLF for ten years or more is indispensable for strategic planning and policy formulation, besides making infrastructure investments (Wang K. et. al., 2023; Lindberg et. al., 2019). Policy development and strategic planning, together with the development of infra-projects, depend on this type of forecasting. LTLF usually incorporates econometric models considering demographic trends, economic indicators, and technological advancements (Agrawal et. al., 2018; Hong et. al., 2013; Zhang et. al., 2023). Other methods widely applied in long-run forecasting include end-use models that forecast demand based on the anticipated usage of electricity in various sectors and input-output models that analyze the varying interdependency between different economic sectors.

1.3. Overview of Deep Learning

Deep learning (DL), a subset of ML, represents the top of artificial intelligence advancements over the past years. DL is characterized by its use of ANN with many layers, hence the term "deep." These networks are capable of learning from vast amounts of data, identifying patterns, and making decisions with minimal human intervention. The transformative potential of DL spans various domains, including computer vision, natural language processing, healthcare, and autonomous systems. At the heart of DL are neural networks, which are inspired by the human brain's structure and function. A typical neural network consists of an input layer, multiple hidden layers, and an output layer. Each layer is composed of neurons that process input data through weighted connections, applying an activation function to produce an output. The network learns by adjusting these weights based on the error between the predicted and real outputs. DL models differ from traditional neural networks in their depth, i.e., the number of hidden layers they contain. The most used DL architectures include Convolutional Neural Network (CNN), which excel in image recognition tasks, and Recurrent Neural Network (RNN), which are well-suited for sequential data like time series and text. CNN is specialized for processing grid-like data, such as images. They employ convolutional layers to automatically and adaptively learn spatial hierarchies of features from input data. CNN of components are convolutional layers, pooling layers, and fully connected Layers. Convolutional layers apply convolution operations to extract features. Pooling layers downsample the spatial dimensions to reduce computation. Fully connected layers serve as the final classifier or regressor. RNN is designed to handle sequential data by maintaining a hidden state that captures information from previous time steps. They are particularly effective for time-series analysis and natural language processing. Variants of RNN are Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU). LSTM addresses the vanishing gradient problem by using gates to control information flow. GRU is a simplified version of LSTM with fewer gates.

Training DL models require large, high-quality datasets. Data preparation involves collecting, cleaning, and preprocessing the data to ensure it is suitable for training. Techniques such as data augmentation, normalization, and splitting the data into training, validation, and test sets are commonly employed. DL models are typically trained using gradient descent algorithms, which iteratively adjust the model's weights to minimize a loss function. Regularization techniques, including dropout and weight decay, help prevent overfitting by constraining the model's complexity. Hyperparameters, such as learning rate, batch size, and the number of layers, significantly impact a model's performance. Hyperparameter tuning involves systematic experimentation to find the optimal configuration. Methods such as grid search, random search, and Bayesian optimization are commonly used to automate this process.

1.4. Deep Learning Techniques in Electricity Load Forecasting

Deep Learning (DL) techniques have revolutionized the field of ELF because of their ability to offer models for complex patterns in data. Table 1.1 lists many of the deep learning techniques developed until now in ELF, which, along with their description, advantages, disadvantages, and applications, are discussed. Each technique carries its unique strengths and shortcomings, and the choice of the method depends upon the specific requirements and constraints presented by the forecasting task. Merging several methods generally provides a greater level of accuracy and robustness than individual models. With the field continuing to grow and evolve, this class of DL methods is likely to increase the contribution it can bring toward enhancing the accuracy and efficiency of ELF.

Table 1.1. Deep learning techniques in ELF.

Technique	Description	Benefits	Limitations	Applications
CNN	Typically used for image processing but can extract features from time series data over short windows.	Captures local patterns well. Useful in combination with other models.	Less effective alone for long-term patterns. Best in hybrid models.	Feature extraction in hybrid models. Short-term load patterns.
LSTM	Addresses RNN limitations with memory cells for long-term dependencies. Effective in	Effective for long-term patterns. Mitigates	Complex architecture. Computationally intensive.	LTLF. Capturing seasonality and trends.

	capturing long-term patterns.	vanishing gradients.		
Recurrent Neural Network (RNN)	Designed to handle sequential data, capturing temporal dependencies. Struggles with vanishing gradients.	Good for sequential data. It can model temporal dependencies.	Vanishing gradients. Limited long-term dependency modeling.	Basic time series forecasting. STLF.
Recurrent Fuzzy Neural Networks (RFNN)	Combines fuzzy logic and neural networks to handle uncertainties and non-linearities in time series data.	Handles uncertainties well. Good for non-linear time series forecasting.	Complex architecture. Requires careful tuning of fuzzy rules and neural network parameters.	Handling non-linearities and uncertainties in load data. MTLF and LTLF.
GRU	A simplified variant of LSTM with fewer parameters. Efficient and effective in capturing long-term dependencies.	Computationally efficient. Comparable performance to LSTMs.	Simpler than LSTMs but still complex. Requires careful tuning.	STLF and LTLF. Efficient implementations.
Attention Mechanisms	Enhances model performance by focusing on relevant input data parts. Improves accuracy by emphasizing important features.	Improves model focus on important features. Enhances accuracy.	Adds complexity. Requires careful implementation.	Highlighting seasonal patterns. Incorporating external factors.
Transformer Networks	Uses self-attention mechanisms to handle dependencies in sequential data	Handles long-range dependencies well. Parallelizable,	Requires large datasets and computational resources. Complex architecture.	Capturing complex dependencies in load data. Handling large-scale datasets.

	without relying on recurrence.	leading to faster training.		
Deep Belief Network (DBN)	Composed of multiple layers of stochastic, latent variables. It can pre-train layers in an unsupervised manner before fine-tuning with supervised learning.	Good for feature learning and dimensionality reduction. Pre-training helps with convergence.	Training can be time-consuming. Requires large amounts of data.	Feature extraction. Pre-training for other DL models.
Autoencoders	Neural networks are designed to learn efficient codings of input data. It can be used for dimensionality reduction and feature extraction.	Effective for unsupervised learning. It can learn complex representations.	Risk of overfitting. Requires careful tuning of the architecture.	Anomaly detection in load data. Feature extraction for forecasting models.
Generative Adversarial Network (GAN)	Composed of a generator and a discriminator network competing against each other. It can generate synthetic data resembling real load patterns.	It can generate realistic synthetic data for training. Useful for data augmentation.	Training can be unstable. Requires careful balancing of generator and discriminator.	Data augmentation for load forecasting models. Generating synthetic load scenarios for testing.
Echo State Network (ESN)	A type of RNN where the hidden layer is a randomly generated, fixed, large, and sparsely connected reservoir.	Simpler to train compared to traditional RNNs. It can handle non-linear time series data effectively.	Requires careful tuning of the reservoir properties. Limited theoretical understanding.	Real-time load forecasting. Capturing non-linear dynamics in load data.
Temporal Convolutional	A type of convolutional	Handles long-range	Requires large amounts of data.	LTLF. Capturing

Network (TCN)	network specifically designed for sequential data with a focus on temporal dependencies.	dependencies with reduced vanishing gradient issues.	Complex architecture.	hierarchical temporal features.
Bidirectional RNN (BRNN)	Consists of two RNNs, one processing the sequence from start to end and the other from end to start.	It can capture information from both past and future states. Enhances context understanding.	Increased computational complexity. More demanding in terms of resources.	Capturing full context in load data. Improved accuracy in short and medium-term forecasting.
Wavelet Neural Network (WNN)	Combines wavelet transform and neural networks to capture both time-frequency characteristics and non-linear relationships.	Effective in capturing both local and global features in time series data. Good at handling non-stationary signals.	Requires careful selection of wavelet functions. Computationally intensive.	STLF and LTLF. Capturing seasonal patterns and transient events.
Support Vector Regression (SVR)	A type of SVM that is particularly effective for regression tasks, including time series forecasting.	Effective for small to medium-sized datasets. Robust to overfitting and noise.	Requires careful tuning of hyperparameters. It can be computationally intensive for large datasets.	MTLF. Handling noisy and small datasets.
Extreme Learning Machine (ELM)	Single-hidden layer Feed Forward Neural Network (FFNN) with random weights in the hidden layer. Efficient training process.	Extremely fast training process. Good generalization performance.	Limited by random weight initialization. May not be as powerful as DL models for complex tasks.	Real-time load forecasting. Fast training for quick model updates.
Hybrid Models (e.g., CNN-LSTM, CNN-GRU)	Combines strengths of different architectures. Uses CNNs for	Leverages strengths of multiple models.	Increased complexity. Requires more	Combining local and long-term patterns.

	local patterns and RNNs for long-term dependencies.	Superior performance.	computational resources.	Improved accuracy.

CNNs were initially designed for image processing but were further applied in ELF by time series forecasting (Khan et. al., 2019; Li et. al., 2017; Tudose et. al., 2020). They successfully capture short-term patterns due to their ability to model local structures within small windows of data; thus, they become instrumental in short-term load pattern identification. However, CNNs alone are not very useful in long-term forecasting tasks unless combined with another model because they might limit long-term dependencies. The hybrid models that use CNN for extracting features and the other networks for long-range dependencies work much better.

LSTM networks are the category of RNN, specially designed to work on deficiencies found in general RNN concerning vanishing and exploding gradient problems. LSTMs are very good for capturing long-term dependencies in time-series data, central to accurate long-term ELF (Muzaffar and Afshari, 2019; Lin et. al., 2022; Ageng et. al., 2021). While very powerful, LSTMs are complex in architecture and require enormous computing power, thus being computationally intensive by nature.

Additionally, it is relevant to note that RNNs are designed to suit time series forecasting by handling sequential data by capturing the temporal dependencies (Khan et. al., 2013; Sehovac and Grolinger, 2020). However, they often suffer from vanishing and exploding gradient problems, hence an inability to capture long-range dependencies. While they perform great in short-term forecasting applications, their limitations in modeling long-term dependencies reduce their positive impacts on long-term forecasting.

A combination of fuzzy logic and neural networks in designing an RFNN yields a solution for uncertainties and non-linearities in time series data. They are pretty effective in dealing with the inherent uncertainties in the time series of electricity load data, providing robust medium- and long-term forecasting (Wen et. al., 2020). However, their complex architecture needs careful tuning of both parameters for fuzzy rules and neural networks (Sharma et. al., 2020).

GRUs are designed to refine LSTMs, with fewer parameters, making them less computationally expensive, yet they maintain effectiveness in capturing long-term dependencies (Kumar et. al., 2018; Gao et. al., 2019). They practically offer the same performance as LSTMs but with simpler architecture and so have proven to be a good candidate for solving both STLF and LTLF problems. Still, they require pretty careful tuning to converge in practice.

Attention mechanisms generally improve the performance of neural networks by guiding them to focus on relevant parts of input data (Zang et. al., 2021; Niu et. al., 2022). In ELF, they will be used to enhance model accuracy by focusing on essential features, such as seasonal patterns and external drivers. However, during the process of incorporating an attention mechanism, the model is going to become complex and meticulous in implementation (Zhang et. al., 2021; Wan et. al., 2023).

The efficiency of transformer networks is highly increased for learning long-range dependencies in sequences through self-attention mechanisms, which are not recurrent. They are parallelizable and make learning much faster. However, modeling with transformers is better with more extensive datasets, and it consumes enormous computational power due to its vast architecture (Zhao et. al., 2021; L'Heureux et. al., 2022; Wang et. al., 2022).

DBNs comprise multiple layers of stochastic, latent variables that can be pre-trained unsupervised before fine-tuning with supervised learning. This makes them well-suited for dimensionality reduction and feature learning. Meanwhile, DBNs require large amounts of data and are slow for training; therefore, they may not be helpful for real-time applications (Kong et. al., 2019; He et. al., 2017).

Autoencoders are unsupervised neural networks designed to learn efficient input data codings for dimensionality reduction and feature extraction. They are efficient for executing complex representations but prone to overfitting and require careful architecture tuning (Tong et. al., 2018; Liu et. al., 2019).

In GANs, the generator and discriminator network fight with each other to generate synthetic data resembling actual load patterns. This can be handy for data augmentation, making the models for load forecasting very robust. However, GANs are very tricky to train, and the balance between the generator and the discriminator is delicate (Xian et. al., 2024; Bendaoud et. al., 2021).

ESN is a particular type of RNN model, where the hidden layer is built as a large and sparsely connected reservoir. These make them easier to train than traditional RNNs and effective in handling non-linear time series data. However, ESNs require delicate tuning of the reservoir properties and have limited theoretical understanding (Deihimi and Showkati, 2012; Bianchi et. al., 2015).

TCNs are convolutional networks with a specifically designed architecture for sequential data, focusing on temporal dependencies. They can handle long-range dependencies and mitigate the vanishing gradient issue. However, TCNs require data, and the architecture is complex, which creates implementation barriers (Tang et. al., 2022; Shi et. al., 2021).

BRNN processes a sequence in two steps: one from start to end and the other from end to start. Hence, it can consider information from both past and future states. This bidirectional approach enables the model to learn the dependencies within a context and improves forecasting. On the other hand, this increases the computational complexity and resource demands (Tang et. al., 2019a; Tang et al., 2019b).

A WNN comprises wavelet transforms and neural networks, which embody both the time-frequency characteristics and the nonlinear relationship in the data. They will work well with non-stationary signals and are capable of extracting local as well as global features: suitable for STLF and LTLF. It is computationally intensive and nontrivial to select appropriate wavelet functions (Guan et. al., 2012; Ribeiro et. al., 2019).

SVR is an SVM for regression and is effective on problems such as time series prediction. The model is robust against overfitting and noise, suitable for datasets of small and medium sizes, and only requires cautious tuning for the hyperparameters. It is sometimes computationally intensive for large dataset sizes (Luo et. al., 2023; Ceperic et. al., 2013).

In the ELM, all the hidden-layer nodes have random weights, such that the training process in an ELM is speedy. It gives the best generalization performance and suits real-time load forecasting in the best manner. However, the initialization of weights is random for complicated tasks (Li et. al., 2016; Zhang et. al., 2013).

Hybrid models provide the best of both worlds of model architectures, just like using CNNs for local pattern extraction and RNNs for capturing long sequences. By the way, these models exploit the advantages of several models and offer better performance. However, the complexity increases with this, therefore requiring higher computational resources, which overall makes it more difficult to implement (Al Mamun et. al., 2020; Ren et. al., 2021; Agga et. al., 2021).

1.5. The Objective of the Thesis

This study has been conducted to enhance further the accuracy and reliability of the Adana, Mersin, and Antalya provinces' ELF models. The study is being done for electricity consumption for lighting, residential, industry, agriculture, and commercial sectors. The novelty in this approach is bringing the DL techniques of LSTM, CNN, and a hybrid model of LSTM and CNN. By exploiting the capabilities of these models, the research will address the distinctive demand patterns and varied energy consumption across various sectors. LSTM boasts the ability to process time series data for long periods. Thus, it applies to most forecasting tasks whose historical load conditions have a significant influence on future demands. On the other hand, CNNs can identify patterns in multidimensional data, and this application in load forecasting brings out hidden patterns in monthly load data that ordinary forecasting methods cannot establish. This method is likely to benefit the industrial and commercial sectors, where the load patterns are complex and highly variable.

The main defined objective is that of experimentation on a hybrid CNN-LSTM model. It utilizes LSTM's strength in framing sequence prediction power and CNN's ability to extract features efficiently. The hybrid model is meant to improve forecasting accuracy by capturing, in the best way, the temporal dynamics and spatial correlations found in the data. This study investigates if this joint approach provides a boost over using LSTM or CNN models individually.

The proposed methods use an extensive dataset in which monthly electricity consumption data for diverse sectors are included from the year 2016 to the year 2023. An enormous database enables the determination of the historical consumption pattern, which is more than necessary to develop more precise forecasting models specifically designed according to the characteristics of the Adana province. A MATLAB/Simulink model is developed to simulate the electrical load profile, enabling detailed observation and analysis. Based on the model, the load forecasting results become adequate consultants that tell what is needed for energy management plans, designs, and policies in Adana Province.

Accurate prediction of future electricity demand allows companies and policymakers to manage energy resources more effectively, sustainable growth planning, and effective energy conservation mechanisms. This research is aimed to reach out to the operational strategies of energy management for the promotion of advanced machine learning techniques. In this respect, the study infers that DL models are good at predicting accurate and reliable load, advocating for a transition toward data-driven and predictive methodologies in energy.

1.6. The Outline of the Thesis

The thesis is designed to offer a detailed study in ELF for Adana, Mersin, and Antalya provinces using advanced DL. It starts with the introduction providing the importance of the ELF and the different types of forecasting, to ultimately explain the use of DL techniques using LSTM and CNN-based techniques. The objectives of the research are clearly stated, followed by an overview of the thesis structure. The literature review covers traditional methods and recent advancements in load forecasting, providing context for the current study. Moreover, the literature review comprehensively covers recent studies, traditional methods, and recent advancements in load forecasting, emphasizing the context and justification for using DL techniques. The materials and methods section details the MATLAB/Simulink dynamic model used for simulation, the data source and preparation, and in-depth discussions of the LSTM, CNN, and the hybrid CNN-LSTM model. The following section will discuss the results of the simulation, the results of the CNN, LSTM, and hybrid models, and a comparative analysis. The key findings will be summarized with a highlight of the effectiveness of the proposed models in improving forecasting accuracy. Finally, the paper outlines some recommendations for improving energy management practices using advanced time-series forecasting models.

2. LITERATURE REVIEW

In recent years, it has been of paramount importance to perform accurate electrical load forecasting to operate and manage power systems efficiently. Reliable load forecasting is the key to maintaining a stable and cost-effective energy distribution. Various studies found in the literature deal with the methodologies for forecasting electrical demand, namely, through statistical methods, ML algorithms, and hybrid models which seek to enhance prediction accuracy.

The newly developed technique being used is Nonlinear Relationship Extraction (NRE) to implement accuracy in the forecasting of residential loads. The methods employ load cubes, which combine hourly load data from different periods and CNNs to detect nonlinear load patterns. The above methods use load-temperature cubes to reveal the hidden relationships between load and temperature. These extracted features are then fed to an SVR model based on input-output mapping for forecasting. The NRE method has so far proven its consistency in outperforming models like LSTM, CNN, FFNN, and SVR to make an accurate one-hour-ahead ELF (Imani, 2021).

Wang D. et al. (2023) proposed a new power demand forecasting model named CNN-LSTM to enhance predictive accuracy in environments with multi-source data. The proposed model combines multimodal information (time series and textual data) through the feature extraction ability of CNN and the long-term memory ability of LSTM networks. Empirical results attest that the identified model substantially outperforms traditional time series models in accuracy, both in direction and magnitude. The model gives valuable insights that can help forecast China's energy demand, which would either slow down in growth or experience a decline over the next couple of years. All these data-driving approaches for proper guidance on the Chinese case of coal power phase-out and renewable energy investments for setting up the overall Chinese energy systems planning and low-carbon transition.

The study by Zhang et al. (2023) presents a deep-learning architecture for ELF. It integrates CNN and LSTMs and uses multi-task learning to deal with problems known for data redundancy and lack of good results in convolution. The CNN layer extracts input data characteristics, and the LSTM layer controls sequence learning. The generalizability and accuracy of the model can be further enhanced by the optimal balancing of essential training data between the primary and auxiliary tasks. The model has also done well in short-term (10 days) and medium-term (3 months) forecasting against other models.

Yazıcı et al. (2022) studied the increased application of DL with STLF, a more complex form of TSP. The problems of such a nature are usually accustomed to LSTM and GRU models, and it was a system using significant breakthroughs for introducing one-dimensional CNN, which Video Pixel Networks inspired. From the comparative analysis, it came out that one-dimensional CNN had the best performance for this time series forecasting problem, particularly for the 24-ahead prediction, and the best model was recorded at a MAPE of 2.21%. Although the CNN performed well in one-hour-ahead predictions with an estimated MAPE of 1.0%, the model difference was not much. This study highlights the possibility of enhancing STLF accuracy through CNNs with a one-dimensional arrangement.

Bouktif et al. (2018) suggested a forecasting process based on ML techniques that rely on LSTM neural networks with precise STLF aggregate electricity load predictions. More recently, the study concerns advanced predictive performance baselines, linear and nonlinear ML algorithms, feature selection methods like wrappers, and embedded ways with a genetic algorithm for optimizing time lags and LSTM layers towards this objective. In the application, a model using LSTM outperformed other optimized ML models concerning empirical accuracy in the case of electricity consumption data from metropolitan France.

Bouktif et al. (2020) describe an improved approach for very short-term electricity consumption forecasting with an LSTM model. The most crucial step in successfully developing the forecasting model remains the identification of good lags and hyperparameters. In addition, to overcome this challenge of finding suitable parameters in discrete search spaces, the authors use metaheuristics for parameter calibration with the GA and PSO methods. In general, these strategies help to find optimal parameters in the complexity of the search space. Input lags are also flexibly selectable through zero-padding and variable length sequences with GA and PSO calibrations of a multi-sequence input model, further enhancing LSTM's capability in capturing long-term dependencies within load consumption patterns. Therefore, overall forecasting is achieved with higher accuracy using this metaheuristic-based calibration approach.

Aguilar Madrid and Antonio (2021) elaborate on a set of ML models developed to increase the forecasting accuracy of 168-hour ahead STLF, which is vital in the planning of power plants. The models use a combination of data from other sources, such as the historical load, the weather, and holidays. Of the five models tested, the Extreme Gradient Boosting Regressor algorithm performed the best, outstripping the predictions from any of the neural network-based models. This ultimately reduces the uncertainty in renewable energy production, lowering hydrothermal electricity costs.

Sajjad et al. (2020) described a sequential hybrid learning model of energy forecasting with a coupling of CNN and GRU. In this case, the algorithm runs in two-step sequences: data preparation and training. Data preparation is carried out to enhance the quality of raw data. Then, extracted features are input into a multi-layered GRU to consume energy accurately. The structure of GRU facilitates improved learning from sequences. As future work, the study will be carried forward with the model applied to other datasets, made more effective by the inclusion of concepts of fuzzy logic.

Alhussein et. al. (2020) propose a hybrid DL framework for short-term ELF using CNN and LSTM layers. The CNN layers in the proposed model extract features, and the LSTM layers take care of the sequence learning. The proposed CNN-LSTM model showed significant improvements in forecasting accuracy with the other state-of-the-art techniques, using publicly available data from a Smart Grid Smart City project. For instance, in the individual household electric load data, it achieved a MAPE of 40.38%, outperforming the former benchmark LSTM-based model, with a MAPE of 44.06%. It additionally proposed using clustering analysis based on energy usage behavior for a more insightful prospect of gaining increased predictive accuracy with more computational power.

An innovative approach for the STLF of a regionally integrated energy system with interconnected energy sources is proposed by Wu et al. (2021). This model utilizes an attention-based CNN combined with an LSTM and BiLSTM to capture the time-sequence and nonlinear characteristics of the electric load. It requires historical data on electric load, temperature, cooling load, and gas consumption over the last five days as inputs. The CNN extracts the attentive load effect factors of the equipped attention block. The LSTM-BiLSTM layers are for forecasting the load one hour ahead. This method shows superior performance to the former ones because it can comprehensively feature the historical data and enhance load forecasting accuracy by introducing the combination of the CNN-attention and LSTM-BiLSTM architecture.

Jawad et. al. (2021) analyzed the influence of meteorological parameters on the ELF through data examination and developed an ML algorithm to optimize the selection of a cost-effective predictive model. The study is based on historical data from the electricity demand of a substation in Muzaffarabad, Pakistan, and weather data for 2014–2015. Data correlation-based evaluation of several ML algorithms. The analysis shows a very high correlation of electricity consumption with some weather parameters, particularly the air and dew point temperatures. It also finds that incorporating the same for model data has caused significant minimization of the prediction errors.

Saglam et al. (2024) study the development of more precise short-term forecasts of electricity peak loads over various ML models and optimization methods. This research comes one step ahead to see the impact of the input combinations on the accuracy of peak load prediction using multilinear regression (MLR) by investigating data from 1980 to the end of 2020, including import/exclude figures, population statistics, and GDP. It is compared with several optimization algorithms using, for instance, PSO, Dandelion Optimizer DO, gold rush optimizer (GRO), and conventional ML models such as SVR and ANN. From the results obtained, the lowest statistical errors are achieved by GRO and ANN, and GDP shows a strong positive correlation with the peak load. Adequate prediction of peak load thus prevents excess reserves and results in the effective management of the electricity network.

A series of hybrid optimization algorithms was presented by Kottath et al. (2023) that embed the Cuckoo Search Algorithm (CSA), Grey Wolf Optimization (GWO), Harris Hawks Optimization (HHO), and Whale Optimization Algorithm (WOA) to enhance the performance of the forecasting models. The investigators allowed particles to update their positions with various algorithms, tested several combinations on 24 benchmark functions, and applied them to short-term electricity load and price forecasting on ANNs using a dataset from ISO New Pool New England to the results that the hybrid algorithms are the best generally than its components, and in which the CSA-GWO showed influential trends. The authors suggest hybrid approaches should be more explored for classification, regression, and optimization tasks in the future.

A three-stage model proposed by Yıldız (2023) provides accurate and effective short-term ELF. VMD is used to extract the features of historical load data. In the second stage, stacked Kernel ELM auto-encoders carry out unsupervised feature learning, which informs the third stage of the kernel ELM regression model for prediction. This paper tests a DL-based MLKELM with public electricity load data from the Turkish transmission system operator. The proposed model has outperformed existing deep ELM architectures and traditional models, such as ANN, SVM, and regression trees, with higher accuracy and sensitivity in forecasting.

Gul et al. (2021) investigate mid-term electricity consumption forecasting using data from Korea Electric Power Supply focusing on Seoul. This study investigates how a statistical ARIMA model could be compared with a neural network combining CNN with Bi-LSTM to optimize the hyperparameters of both models for improved predictive accuracy. The results showed that, on the one hand, ARIMA involves much preprocessing but furnishes credible results if patterns within the data are somewhat consistent. The combination of CNN-LSTM did not perform very well, thus verifying the fact that proper model selection and tuning need to be done accurately. In practice, both models, though, have shown potential, especially ARIMA, for applications in which electricity consumption patterns are relatively stable.

In another study in the literature, Nti et al. (2020) reviewed 77 academic studies performed between 2010 and 2020 on electric demand forecasting. They study forecasting algorithms, theories, and factors influencing electricity consumption, accuracy and error metrics, and forecasting periods. Other studies have found that the favorite forecasting models applied artificial intelligence techniques, of which 28% were based on ANN, especially in the short term. The weather, economic parameters, history of consumption, lifestyle in households, and stock indices influence electricity demand forecasting. The authors conclude that ELF is a complex yet important research area seeking further investigation to face the ongoing challenges and exploit new opportunities within the field.

The study conducted by Liu et. al. (2023) proved the method to improve ELF, employing backpropagation neural networks with major meteorological factors. The preset point, which affects electricity load the most during summer, is temperature. As far as the prediction of power load is concerned, the neural network performs much better than other methods. This study recommends the use of Pearson correlation in the analysis of meteorological factors so that influential variables can be identified based on geography and time to further increase forecasting accuracy. Additionally, as big data continues to expand, other relevant factors may be incorporated into the future models and the interconnections studied to enhance load forecasting precision.

Huy et. Later, Al. (2022) proposed the Temporal Fusion Transformer, a new RNN architecture to predict short-term power loading in Hanoi, Vietnam. It shows a model that marries current models like LSTM to the self-attention mechanism, embedded features like temperature, humidity, calendar, lunar months, day of the week, and hours. At the same time, it considers the holidays separately. As evidence, the results of this study prove that the TFT significantly performed better in terms of Mean Absolute Error (MAE) and MAPE compared to the traditional statistical models and the established RNNs. Further research shall consider the improvement of the model's accuracy during holidays and unexpected events like COVID-19.

Kong et al. (2017) focused on short-term ELF in individual residential households whose energy consumption was so volatile and unpredictable. They propose a framework based on LSTM RNN, a DL method capable of managing long-term, temporal patterns. Testing the effectiveness of their approach on publicly available intelligent metering data is made and compared against another state-of-the-art algorithm. They highlight the contrast using a density-based clustering technique between the aggregate load at the substation level and volatile individual loads. Future work seeks to design better parameter-tuning techniques for the fine-tuning of predictions, specifically for very unpredictable households.

The study conducted by Mujeeb et al. (2019), used Deep Long, Short-Term Memory (DLSTM) for electricity price and load forecasting within energy big data from smart grids. In doing so, the model applied the learned attributes through DLSTM for hyperparameters and those features that need automatic tuning when handling a vast dataset. It contributes to handling training challenges and guarantees model stability under the cross-validation method; its practical validity is very well supported by solid performance in actual market data coming from New York and New England operators. This type of model includes preprocessing of data, training, and forecasting of load and price patterns over 24, 168, and 744 hours. Results are measured using the MAE and Normalized Root Mean Square Error (NRMSE) metrics, where it is seen that the DLSTM model outperforms compared to traditional forecasting methods, namely the Nonlinear Autoregressive network with Exogenous variables, and ELM, with improved accuracy.

This review now consolidates much more extensive work into a more focused form by presenting detailed narrative summaries of various methodologies and their specific contributions to ELF. Table 2.1. Organized summary of references: An organized summary of references is an excellent tool for a comprehensive but very effective comparison of different forecast techniques and their output. This table format allows easy access to data and an immediate visual comparison of methods, results, and critical findings across studies. When looking at such studies in a table, readers could immediately notice the trend, gap, and correlational patterns of the current research landscape, understanding instantly the development of the field and emerging trends of ELF.

Table 2.1. An extensive review of literature on ELF.

Reference	Applied and Developed Methods	Data Source	Key Findings
(Zhang et. al., 2018)	Hybrid model with improved Empirical Mode Decomposition (EMD), Autoregressive Integrated Moving Average (ARIMA), and WNN optimized by the Fruit Fly Optimization Algorithm	Australian Energy Market Operator; New York Market: New York Independent System Operator	The hybrid model provided accurate forecasting results, outperforming other comparative models by effectively combining linear and nonlinear characteristics.
(Dedinec et. al., 2016)	DBN with multiple layers of Restricted Boltzmann Machines (RBMs) and supervised back-propagation	Macedonian Market: Macedonian Hourly Electricity Consumption data (2008-2014) provided by the Macedonian system operator	DBN achieved superior accuracy compared to traditional methods like FFNNs and the data provided by the Macedonian system operator, reducing MAPE by up to 8.6%.
(Fan et. al., 2022)	Ensemble EMD, Random Forest (RF), SVR, Ridge Regression (RR)	New South Wales, Australia, electricity data from 1st to 14th	The EEMD-RF-SVR-RR model achieved superior forecasting accuracy by decomposing the

		January 2007, electricity load data per 30 min	original data using EEMD, and then applying a combination of RF, SVR, and RR algorithms. The model effectively handled data fluctuation and non-linearity, surpassing traditional models.
(Guo et. al., 2020)	Multi-scale CNN-LSTM hybrid neural network: A STLF model integrating CNN and LSTM techniques to improve prediction accuracy	Real-time electricity data of New South Wales, Australia, from 2006 to 2010	The multi-scale CNN-LSTM model outperformed traditional LSTM, SVM, RF, and ARIMA models, achieving higher prediction accuracy and robustness. Incorporating real-time electricity prices improved the model's performance.
(Sun et. al., 2023)	Combines variational mode decomposition (VMD) optimized by the Northern Goshawk Optimization (NGO) algorithm and Kernel ELM optimized by the Sparrow Search Algorithm (SSA)	Collected data from various power terminals	The proposed NGO-VMD-SSA-KELM model achieves higher prediction accuracy for different power consumption types, with RMSE as low as 0.0098 for industrial stations. This approach offers reliable data support for precise load management.
(Aslam Shahzad et. al., 2021)	AdaBoost, Decision Tree, and RF for feature extraction. SVM and CNN with Coronavirus Herd Immunity Optimization (CHIO) for load and price forecasting.	ISO-NE dataset (daily consumption data over 8 years)	The proposed CNN-CHIO and SVM models achieve high accuracy in predicting electricity price and load, with CNN-CHIO showing a 95% accuracy and a 6% MAPE error rate. These models enhance energy

			management and grid optimization.
(Prasetyo et. al., 2023)	Hybrid CNN-BiLSTM with an attention mechanism	Electricity load data from Bali, Indonesia (2018-2019)	CNN-BiLSTM with attention outperforms other models for STLF with RMSE of 12.647-15.381
(Sekhar and Dahiya, 2023)	GWO-CNN-BiLSTM hybrid model	Four buildings: campus, hospital, residential, and industrial from Mendeley and Kaggle	GWO-CNN-BiLSTM performs better than CNN-LSTM, CNN-BiLSTM, and optimized BiLSTM models. Provides accurate STLF across different building types
(Khan et. al., 2023)	Deep residual CNN with stacked LSTM	Individual-Household-Electric-Power-Consumption (IHEPC) dataset and Pennsylvania-New Jersey-Maryland (PJM) dataset	The proposed an innovative two-phase framework with data cleansing and a deep residual CNN architecture to extract spatial features and then a stacked LSTM to capture temporal patterns. The model reduced the error rates significantly across IHEPC and PJM datasets.
(Jung et. al., 2020)	Transfer learning with deep neural networks, Pearson correlation coefficient, pre-training, and fine-tuning.	Monthly electric load data for 25 districts in Seoul, categorized into household, public, industrial, service, and total	The proposed model based on transfer learning, outperforms existing machine-learning models. Improved performance was noted in mid-term load forecasting.
(Fan et. al., 2021)	SVR - Grey Catastrophe - RF modeling	Half-hour load data for New South Wales, Australia (2007) from the Australian Energy Market Operator	The proposed SVR-GC-RF hybrid model for planning for electricity consumption. Outperformed individual models (SVR, RF) with MAPE of 6.35% and

			6.21% in two datasets.
(Memarzadeh and Keynia, 2021)	Wavelet transform to eliminate fluctuations, feature selection based on entropy and mutual information, and LSTM neural networks for load and price prediction.	Load and price data from the Pennsylvania-New Jersey-Maryland (PJM) electricity market, Spain electricity market, and Iran load data.	The proposed hybrid model significantly improved the accuracy of short-term load and price forecasting. The MAPE for load forecasting is reduced to an average of 0.40, and the MAPE for price forecasting is reduced to an average of 0.93.
(Hu et. al., 2022)	Hybrid mode decomposition algorithms based	Electricity load data from industrial enterprises.	The dynamic integrated forecasting model achieved an accuracy as high as 99% in predicting short-term electricity loads. The model provides a reliable basis for optimizing production scheduling by identifying anomalies.
(Haque and Rahman, 2022)	LSTM-RNN	Two commercial buildings in Virginia, USA	The study presents an optimized LSTM-RNN model for 30-minute and 24-hour ELF, incorporating heuristic analysis for feature and hyperparameter selection implementation via TensorFlow for scalable cloud integration.
(El-Azab et. al., 2024)	FFNN, Adaptive Neuro-Fuzzy Inference System (ANFIS), LSTM, and GRUs	ISO New England Control Area Market, from 1 January 2021 to 31 December 2021	The study concludes that forecasting models incorporating external factors such as temperature, day type, and historical data achieve more accurate predictions with lower errors,

			with ANFIS, ANN, LSTM, and GRU excelling across seasons for energy load and electricity price predictions, particularly under non-linear, fluctuating market conditions.
(Lee and Cho, 2022)	Seasonal ARIMA with exogenous variables (SARIMAX), ANN, SVR, LSTM, SARIMAX-ANN, SARIMAX-SVR, and SARIMAX-LSTM	Korea, from 1 January 2014 to 19 October 2019	The study concludes that LSTM-based models, both in single and hybrid SARIMAX-LSTM forms, outperform traditional time series models in forecasting electricity peak loads in Korea, demonstrating superior accuracy, especially in handling sharp fluctuations, and suggesting significant improvement potential for Korea's current forecasting models.
(Behmiri et. al., 2023)	Time-series regressions and FFNNs	Italian Power Exchange, from 1 January 2016 to 31 December 2019	The study reveals that while accurate weather predictions significantly improve STLF, incorporating forecasted temperatures in mid-term models is beneficial but yields diminishing returns, emphasizing the importance of static models with seasonal and external variables for longer-term forecasting.

The diverse methodologies for ELF underscore the continuous advancements and refinements in this vital field. DL models such as CNN, LSTM, GRU, and BiLSTM have significantly improved forecasting capabilities by effectively capturing spatial and temporal dependencies within complex datasets. Furthermore, hybrid approaches have shown notable improvements by merging the strengths of individual models to address the multifaceted nature of load forecasting. Each method offers unique benefits and insights, contributing to the ultimate goal of achieving more accurate, reliable, and scalable load predictions. This comprehensive review highlights the importance of ongoing innovation and the potential for integrating advanced techniques to meet the evolving demands of ELF.

3. MATERIALS AND METHODS

3.1. MATLAB/Simulink Dynamic Model

The MATLAB/Simulink model is presented in Figure 3.1. showcases an integrated power system that combines multiple renewable energy sources with various load profiles over 24 hours. The present Matlab/Simulink model includes an 8 MW photovoltaic (PV) array that converts solar irradiance into energy, a 5 MW wind farm that receives wind profile data, and finally, a 30 MW hydroelectric power plant that provides powerful base load. The high-voltage electrical power produced must be step-downed by a transformer (34.5kV/380V) to properly distribute against diverse loads like lighting, residential, industry, agriculture, and commercial applications. The aggregate powers of these profiles are used in the model to determine the total load, while the outputs of the renewable sources will be summed out to form the aggregate power. The model is developed in MATLAB/Simulink to allow for very detailed dynamic analyses, testing of scenarios by changing inputs, and optimization for greater efficiency and sustainability. Such dynamic simulation model representation supports the development of efficient and sustainable energy systems by modeling the generation, distribution, and consumption of power.

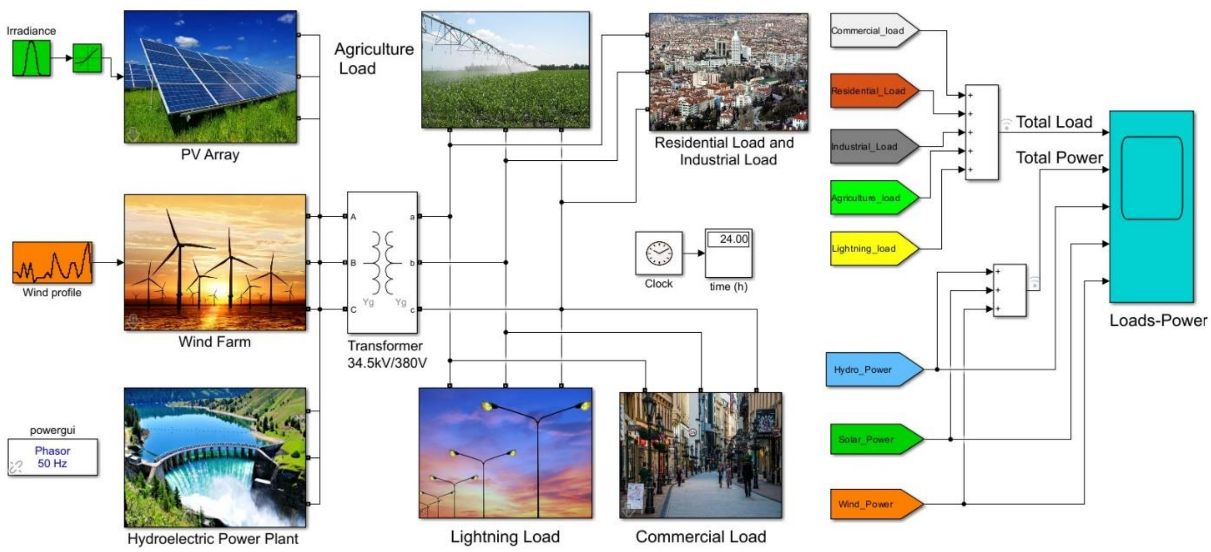


Figure 3.1. The power system incorporating multiple renewable energy sources and diverse load profiles.

This model begins with critical solar irradiance data since it forms one of the inputs without which the performance of the PV array cannot be simulated. Irradiance data changes all through the day and hence affects the power output of the PV panels. The 8 MW installed capacity PV array will convert the sun's energy into electrical power and thereby effectively harness renewable energy from the sun and inject it into the power grid. This power produced is then fed into the various loads in the system. Similarly, data for the wind profile, which shows the speed of the wind in 24 hours, is employed in the model to impact the power output of the wind farm, which is different by the condition of the wind. The 5MW wind farm has turbines installed to trap the wind to the electrical power and further feed into the grid to supply the different load demands.

In the model, the 30 MW installed capacity hydroelectric power plant provides a more stable and controllable kind of power vis-à-vis the variable nature of solar and wind power. An essential part of the model is a transformer, which steps down the high-voltage electricity being generated by renewable sources into a voltage that is safe and fit for distribution. This ensures that residential, commercial, and industry consumers use power safely and efficiently. It consists of a model with load profiles of the lighting, residential, industry, agriculture, and commercial demands. The agriculture loads represent the power consumed in these various activities—irrigation, and machinery that change with the time of the day and the season. The residential load consists of all household appliances for heating and lighting. Industry loads pertain to the use of machinery and production processes. In contrast, commercial loads are indicative of shop, office, and restaurant power uses, with a typical peak during business hours that visibly wanes at night. The lighting load pertains to the street and public lighting requirements.

The total system load is the sum of these load profiles, representing the aggregate power demand that needs to be met through the combined output of the renewable sources. It then sums up the power outputs from the hydroelectric plant, PV array, and wind farm to get the total power generated. The addition should be enough to satisfy a steady power demand. This model is elaborately set up in the MATLAB/Simulink environment to get deep analysis and visualization of the power system dynamic results over a day. The results can be used to simulate the performance and reliability of renewable energy sources, power distribution efficiency, and power supply adequacy. A base model is developed in which scenario testing is done with corresponding inputs of solar irradiance, wind speed, load profiles, etc. These become helpful in accepting the changes or variations in power systems. Findings from such simulations may inform optimization efforts, such as adding more renewable energy sources or improving load management and infrastructure components.

3.2. Data source and preparation

The dataset will be used in this thesis study for electricity load forecasting by the sector loads. The Republic of Türkiye Energy Market Regulatory Agency monthly report under the title "Electricity Market Monthly Sector Report" provides information about electricity consumption data by the sectors of lighting, residential, industry, agriculture, commercial, and total load. It is from January 2016 to December 2023, providing the user with a very wide temporal framework in which to analyze trends and predict future electricity demand (Republic of Türkiye Energy Market Regulatory, 2024).

It chose the data source variable for its authoritativeness and consistency in reports by EMRA; the documents are reliable due to the implementation of standardized compilation methods and detailed insight into electricity consumption patterns by sector. The analysis in this thesis has focused on the sectoral data level to make the realization of a granular level of insight in the design of an accurate forecasting model of electricity load variation.

Data preparation included extracting monthly electricity load entries from the EMRA monthly reports and digitizing the information in a way acceptable for analysis. Monthly electricity consumption for each sector was placed in a time-series format and is now fit to be used in forecasting models. The next step was handling missing or inconsistent data entries. Data was normalized to equalize electricity load value variances in all sectors to enable each model, more so the sensitive models to the scales of input data like CNN-LSTM, to be on a level playing field in comparisons of the electricity consumptions from each sector; this also helps the model to stabilize and converge during training.

To prepare the data for the CNN-LSTM model, the time-series data was segmented into overlapping windows, each representing a sequence of past electricity load values used to predict future values. The sliding window approach was adopted, where each window included a fixed number of past observations as input features and the subsequent observation as the target variable. This method captures the temporal dependencies within the data, which are crucial for the CNN-LSTM architecture to accurately learn and predict future electricity loads. The dataset was split into training and testing sets. The model was trained using the first 78 months of data (January 2016 to June 2022) and tested on the last 18 months (July 2022 to December 2023).

3.3. Long Short-Term Memory (LSTM)

LSTM is a specialized type of RNN architecture designed to effectively capture and learn long-range dependencies in sequential data. Developed by Sepp Hochreiter and Jurgen Schmidhuber in 1997, LSTMs address the limitations of traditional RNNs, which often struggle to retain information over long sequences due to problems such as vanishing and exploding gradients. Unlike standard FFNNs, LSTMs feature feedback connections that allow them to process entire sequences of data rather than individual data points. Through a series of gating mechanisms, LSTMs can regulate the flow of information, enabling them to preserve and utilize significant information over extended periods. Figure 3.2. presents the architecture of an LSTM neural network.

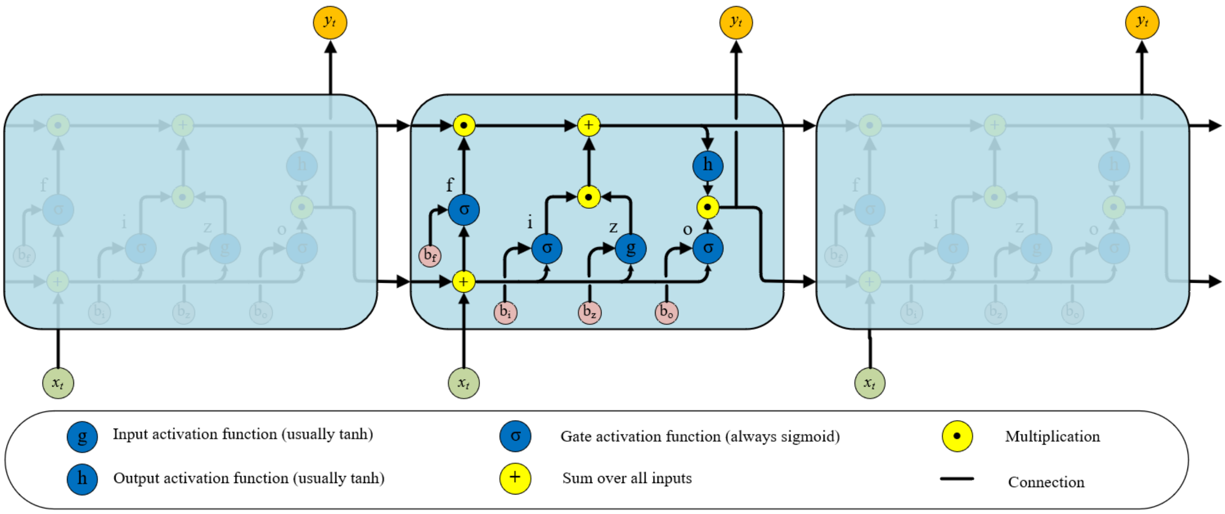


Figure 3.2. The general architecture of LSTM neural network.

An LSTM cell comprises three primary gates: the input gate, the forget gate, and the output gate, illustrated in Figure 3.3., Figure 3.4., and Figure 3.5., respectively. These gates manage the cell state, which functions as the network's memory. The input gate determines which new information should be incorporated into the cell state, the forget gate decides which information should be removed, and the output gate regulates the output based on the cell state and the current input. This gating mechanism allows LSTMs to selectively update their memory, enabling them to learn dependencies in sequences of data that span long durations.

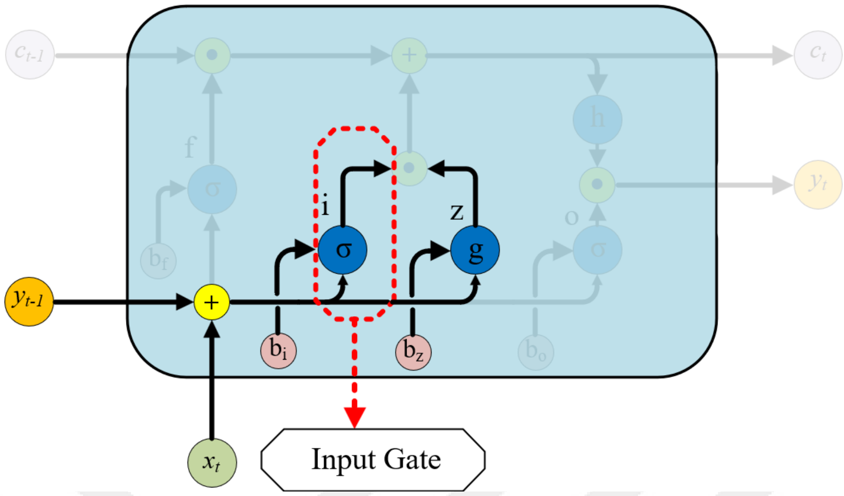


Figure 3.3. The input gate of the LSTM neural network.

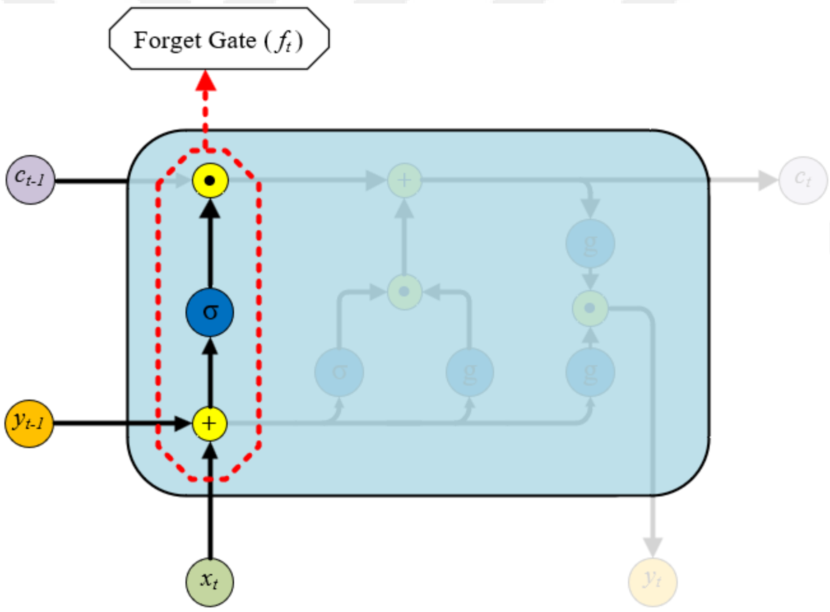


Figure 3.4. The forget gate of LSTM neural network.

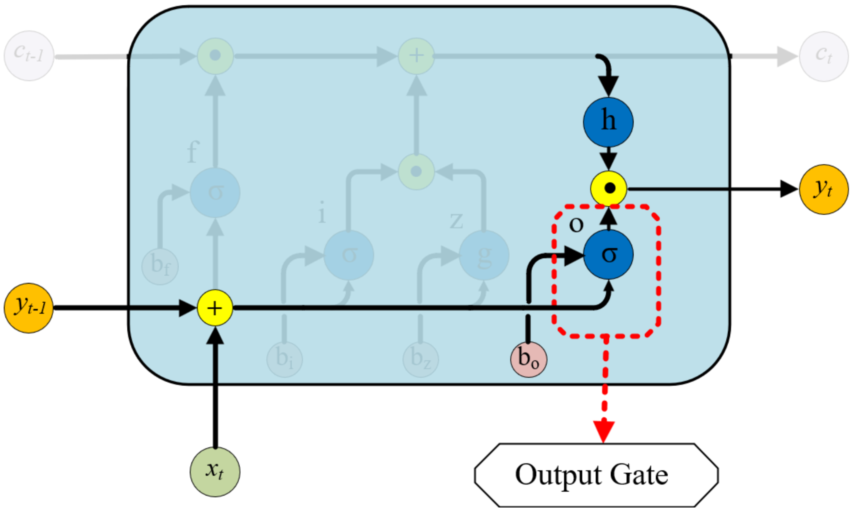


Figure 3.5. The output gate of the LSTM neural network.

The functioning of an LSTM unit can be explained through a series of equations below that dictate how the gates update and interact with each other:

$$f_t = \sigma(W_f.[y_{t-1}, x_t] + b_f) \tag{3.1}$$

$$i_t = \sigma(W_i.[y_{t-1}, x_t] + b_i) \tag{3.2}$$

$$\tilde{C}_t = tanh(W_C.[y_{t-1}, x_t] + b_z) \tag{3.3}$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{3.4}$$

$$o_t = \sigma(W_o.[y_{t-1}, x_t] + b_o) \tag{3.5}$$

$$y_t = o_t * \tanh(C_t) \tag{3.6}$$

Here, f_t represents the forget gate's activation vector at time t, σ denotes the sigmoid function, W_f are the weights associated with the forget gate, y_{t-1} is the previous output, x_t is the current input, and b_f is the bias. i_t is the input gate's activation vector, $\tilde{C}_t$ is the candidate values vector, computed by applying a $tanh$ function. The cell state C_t is updated by forgetting the old state C_{t-1} as dictated by f_t and adding new candidate values scaled by i_t. o_t is the output gate's activation vector, and y_t is the final output of the LSTM unit at time t.

One of the primary strengths of LSTM networks is their capability to effectively manage various sequence prediction problems. In ELF, where historical data is essential for predicting future load, LSTMs excel due to their ability to retain information over extended periods. They have been extensively used in fields such as natural language processing (NLP), speech recognition, and time series forecasting.

In NLP, for instance, LSTMs are employed in tasks like language modeling, text generation, and machine translation. Their proficiency in capturing long-term dependencies makes them particularly adept at understanding context in text, where the meaning of a word can depend on words that appeared much earlier. Beyond NLP, LSTMs are also crucial in speech recognition. Speech signals are sequential by nature, and LSTMs' ability to model long-term dependencies aids in accurately transcribing spoken language.

Moreover, in time series forecasting, LSTMs can discern patterns and trends from historical data, making them effective for predicting future values in domains such as financial markets, weather forecasting, and other areas where data points are temporally correlated. Despite their powerful sequence-handling capabilities, LSTMs do pose challenges, such as being computationally intensive and sensitive to hyperparameter settings, including the number of LSTM layers and units, learning rate, and batch size. Additionally, the accuracy of forecasting can be significantly influenced by how well the training data represents future conditions.

3.4. Convolutional Neural Network (CNN)

CNNs are specialized kinds of neural networks used primarily for processing grid-like data such as images. They have been a fundamental force behind advancements in DL, especially in tasks like image and video recognition, image classification, and natural language processing (Krichen, 2023). A CNN typically consists of an input layer, an output layer, and multiple hidden layers. The hidden layers of a CNN typically involve a series of convolutional layers that convolve with multiplication or other dot products. The activation function is commonly Rectified Linear Unit (ReLU). Pooling layers, fully connected layers, and normalization layers are also frequently used components of CNNs as shown in Figure 3.6. The core building block of a CNN is the convolutional layer that applies a convolution operation to the input, passing the result to the next layer. This layer performs a dot product between the convolutional filter and a small region of the input data. Through training, CNNs learn filters that activate when they detect some specific type of feature at some spatial position in the input. Pooling (or subsampling or down-sampling) reduces the dimensionality of each feature map but retains the most important information. Pooling layers typically use max pooling or average pooling techniques to streamline the underlying computations necessary for processing data through dimensionality reduction. Activation functions such as ReLU introduce non-linear properties to the system. ReLU is favored in CNN architectures due to its computational simplicity and ability to reduce vanishing gradient problems. CNNs automatically detect important features without any human supervision. For instance, in an image recognition task, a CNN might learn to identify edges in its early layers, shapes in middle layers, and specific objects in deeper layers. This hierarchical feature learning is key to their performance. Beyond image processing, CNNs are widely used in recommendation systems, image classification, medical image analysis, natural language processing, and other areas of artificial intelligence.

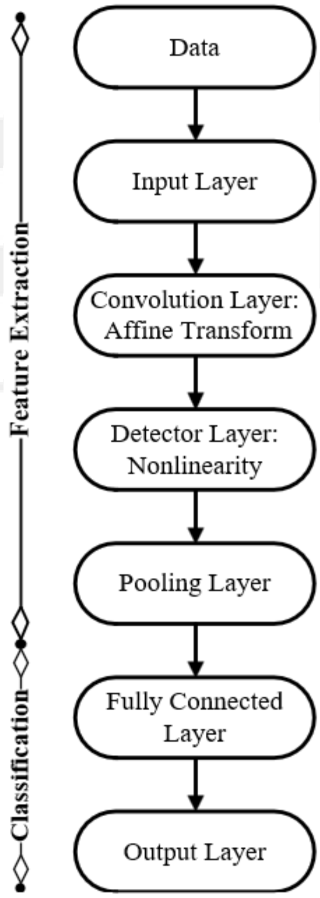


Figure 3.6. Primary functions of a standard CNN architecture.

While CNNs are highly effective, they also present challenges, including the requirement for large amounts of labeled data, susceptibility to adversarial attacks, and the high computational cost of training extensive networks. To mitigate these issues, techniques such as data augmentation, transfer learning, and network pruning are employed. Recent advancements in

CNN architectures include the development of Capsule Networks, which aim to enhance the encoding of spatial hierarchies between features, and the integration of attention mechanisms, which help the network focus on relevant features more effectively (Patrick et. al., 2022).

3.5. CNN-LSTM Hybrid Model

The CNN-LSTM hybrid model is an innovative neural network architecture that merges the strengths of CNN and LSTM networks. This approach effectively combines CNN's feature extraction abilities with LSTMs' sequential processing capabilities, making it particularly suitable for tasks involving both spatial and temporal data. In the realm of ELF, this hybrid model can discern patterns in historical load data and provide accurate predictions for future loads.

The integration of CNN and LSTM into a single hybrid model seeks to leverage the complementary strengths of both architectures. Typically, CNNs serve as the front end to extract high-level spatial features from input data. These features are then fed into the LSTM network, which processes the temporal sequences and dependencies. This hybrid model surpasses traditional and standalone models by handling large and complex datasets more efficiently, thanks to CNNs' robust feature extraction. Additionally, the LSTM component ensures that temporal dependencies are captured, which is crucial for time series prediction tasks. As a result, the model is both powerful and flexible, capable of learning intricate patterns and making precise predictions.

The hybrid model begins with a CNN layer that processes the input time series data to identify local patterns and trends. The input data is structured with a 12-step lag, representing 12 months of past load data, aimed at capturing seasonal patterns and other temporal dependencies. The CNN layer's primary function is to identify significant features from these sequences, which are then passed to the LSTM layers. The CNN component consists of one convolutional layer that uses filters to convolve over the input time series, identifying key features that represent local dependencies in the data. The output from the CNN layer is a set of feature maps, crucial for understanding variations and trends in the electricity load data.

To prevent overfitting, dropout is applied with a rate of 0.5, which randomly sets a fraction of input units to zero during training. Following the CNN layer, the feature maps are fed into an

LSTM layer with 60 neurons. This LSTM layer is designed to capture long-term dependencies and temporal correlations in the time series data, essential for accurate forecasting. LSTMs are particularly effective in handling time series data due to their ability to maintain and update a cell state, which stores long-term information across time steps. The combination of CNN and LSTM enables the model to capture both local and global patterns in the data.

To further enhance the model's generalization capability and prevent overfitting, dropout regularization is employed. With a dropout rate of 0.5, half of the neurons in the layer are randomly dropped during each training iteration. This technique prevents the model from becoming too reliant on specific neurons, thereby improving its ability to generalize to unseen data. Dropout is a critical regularization method in DL models, especially in preventing overfitting in complex architectures like the CNN-LSTM hybrid model.

The model is trained using the first 78 months of the dataset (January 2016 to June 2022) and tested on the last 18 months (July 2022 to December 2023). The training process involves optimizing the model parameters to minimize the forecasting error on the training data. A batch size of 64 is used, which means that the model parameters are updated after processing 64 sequences at a time. This batch-wise training helps in efficiently managing the computational resources and accelerates the training process. The model is trained for 250 epochs, allowing sufficient iterations for the model to learn the underlying patterns in the data.

The CNN-LSTM hybrid model represents a significant advancement in DL, offering a robust solution for tasks involving both spatial and temporal data. Its application in ELF demonstrates its potential to revolutionize this critical field by providing more accurate and reliable predictions.

4. RESULTS AND DISCUSSIONS

4.1. Simulation Results for Dynamic Model

The simulation results from Matlab/Simulink provide a detailed analysis of power generation and load distribution over 24 hours. Figure 4.1. features five distinct power profiles: Total Load (Red), Total Power (Blue), Hydroelectric Power (Orange), Solar Power (Green), and Wind Power (Black). Each profile provides important insights into the dynamics of power production and consumption within the simulated environment.

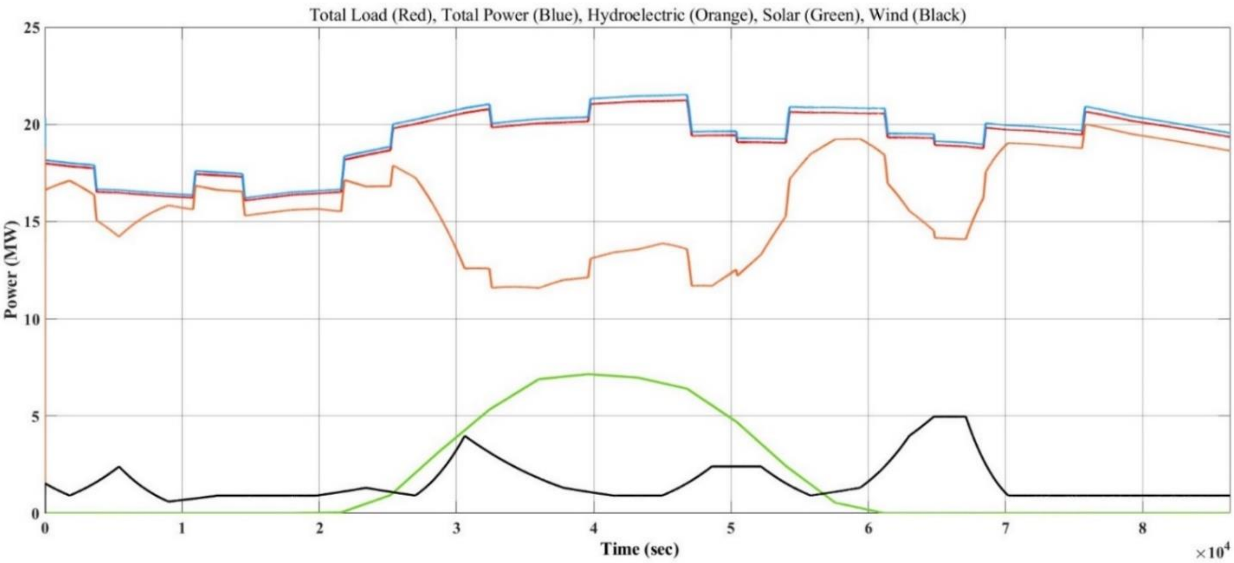


Figure 4.1. The active power results of the dynamic model.

The red line in the graph represents the total load, which fluctuates throughout the day, showing several peaks and troughs that indicate periods of high and low demand. These fluctuations likely stem from varying demands across the agriculture, residential, industry, commercial, and lighting sectors. Notable peaks occur around the midpoints of the simulation period, suggesting higher demand during working hours or periods of increased activity. The blue line, representing total power, closely follows the total load curve with slight deviations. This indicates that the power generation system responds to load demands but may also have some buffering capacity or storage to smooth out these deviations. The close alignment of total power with total load highlights the effectiveness of the power management system in matching generation to demand.

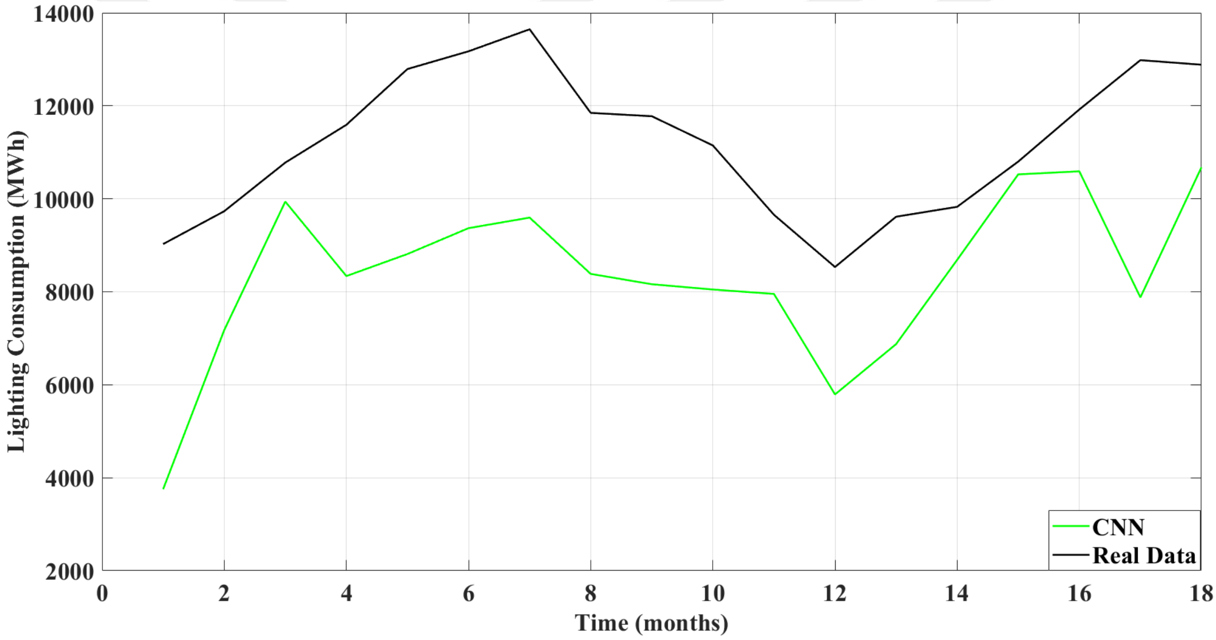
The orange line, depicting hydroelectric power, shows significant variability throughout the day. Hydroelectric output generally increases during high load periods, indicating its role as a primary source of dispatchable power to meet peak demands. However, there are also periods when hydroelectric output drops significantly, possibly due to resource constraints or strategic power management decisions. Solar power generation, represented by the green line, follows a clear diurnal pattern, peaking at midday when sunlight is most abundant. With an installed capacity of 8 MW, the graph shows that solar power output reaches near this maximum capacity around noon. This pattern underscores the predictable nature of solar power but also highlights its dependence on daylight, with zero output at night.

Wind power, shown by the black line, exhibits a more erratic pattern compared to solar power. With an installed capacity of 5 MW, wind power generation varies significantly throughout the day, reflecting the intermittent nature of wind resources. There are periods where wind power output peaks, contributing significantly to total power, and other times where it drops to minimal levels. This variability is typical of wind energy and underscores the need for complementary power sources or storage to ensure a reliable power supply.

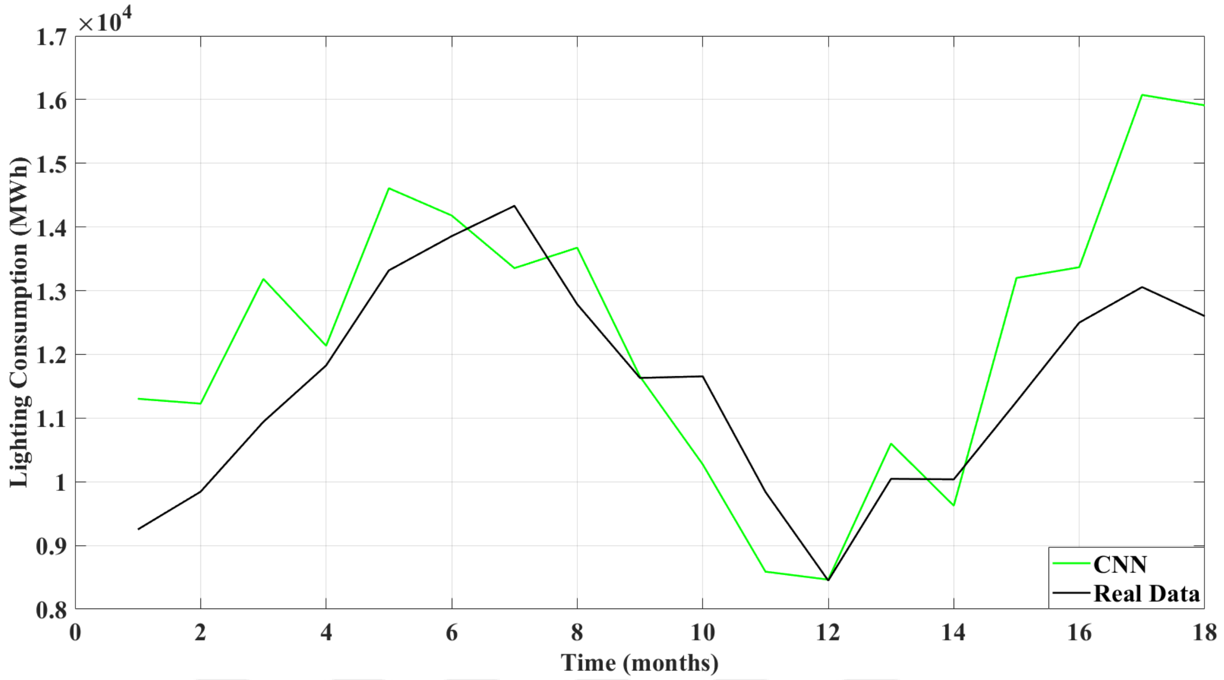
The interplay between these different power sources and the total load reveals a complex and dynamic power system. The combined contributions of hydroelectric, solar, and wind power are managed to effectively meet the fluctuating load demands. During high load periods, hydroelectric power ramps up, while solar and wind contributions are maximized according to their availability. During lower load periods, hydroelectric output is reduced, possibly to conserve water resources or due to lower demand. The ability to balance these power sources is crucial for maintaining grid stability and ensuring a continuous power supply. The simulation results demonstrate the importance of having a diverse mix of power generation sources. Each source has its strengths: hydroelectric power provides reliable, dispatchable power; solar power offers predictable daytime generation; and wind power adds additional capacity, albeit with variability. The Matlab/Simulink simulation results provide a detailed view of how different power generation sources can be effectively managed to meet varying load demands over 24 hours.

4.2. The Results of CNN-Based Electricity Load Forecasting

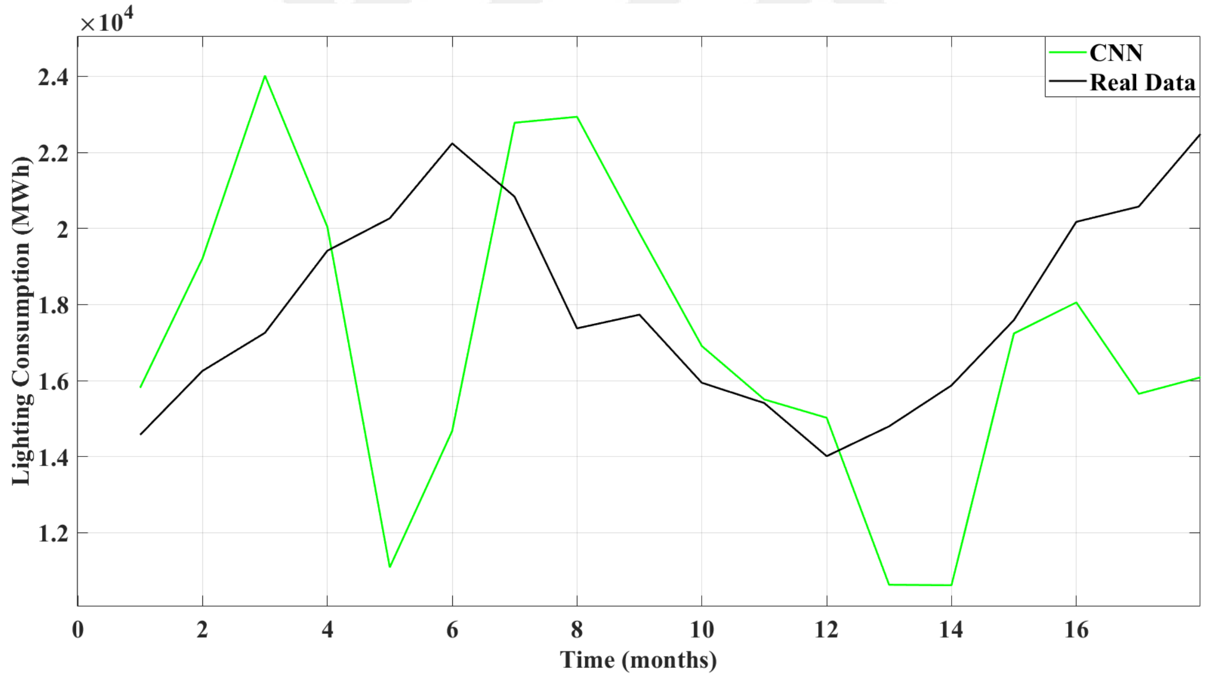
The CNN model has been implemented to forecast sectoral electricity load in Adana, Mersin, and Antalya provinces. The prediction performance of the proposed CNN model over test data for the sectoral electricity load in Adana, Mersin, and Antalya provinces is presented in Figures 4.2-4.7. Figures 4.8-4.13 provide linear regression graphs of the CNN model for the lighting, residential, industry, agriculture, commercial, and total load, respectively. The results indicate that the CNN model provides low-accurate and reliable forecasts for different sectors according to LSTM and CNN-LSTM, demonstrating its deficiency in capturing complex patterns in electricity consumption data.



(a)

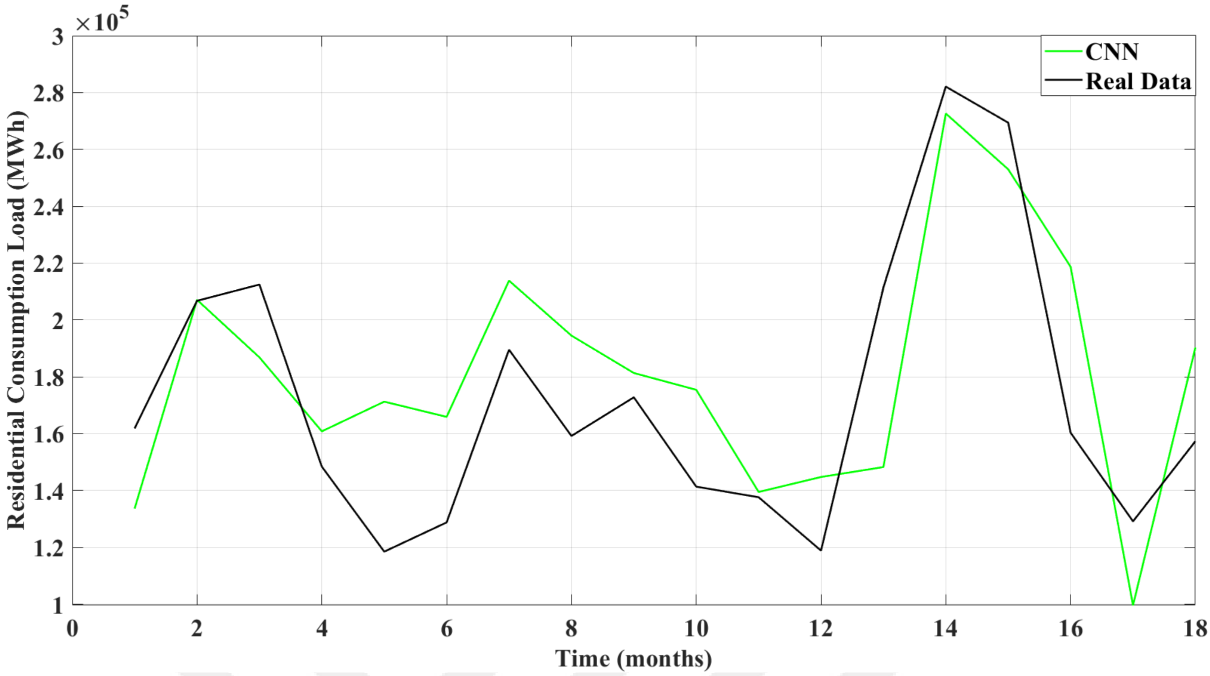


(b)

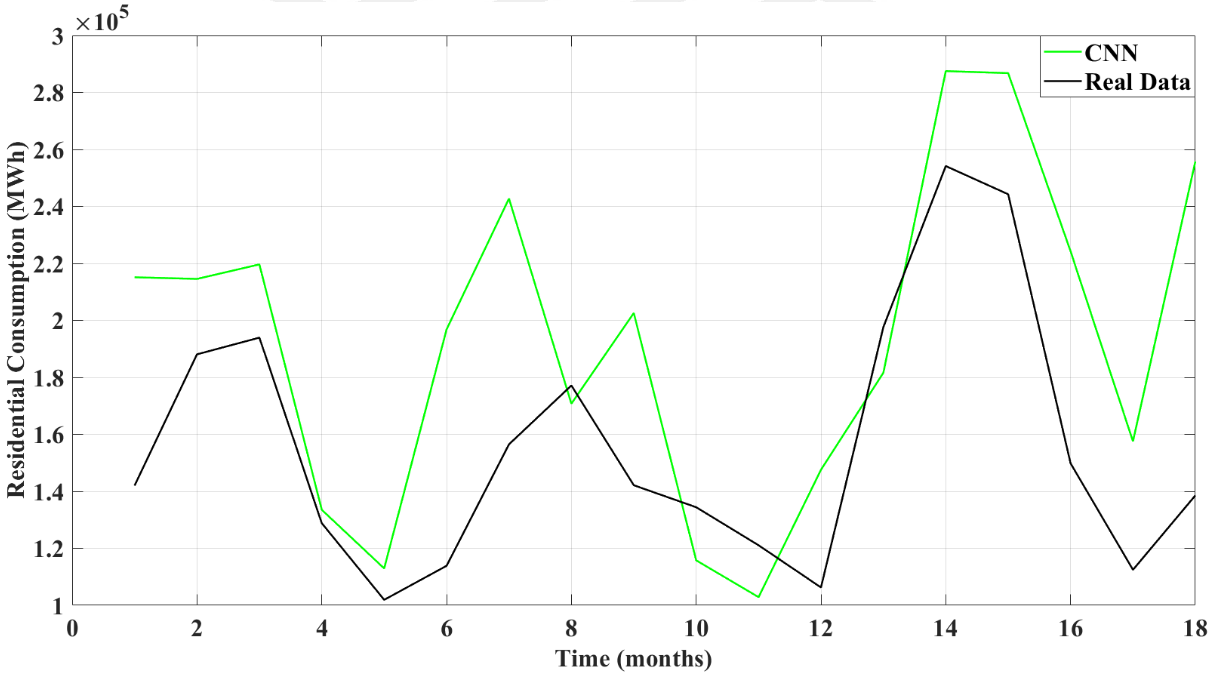


(c)

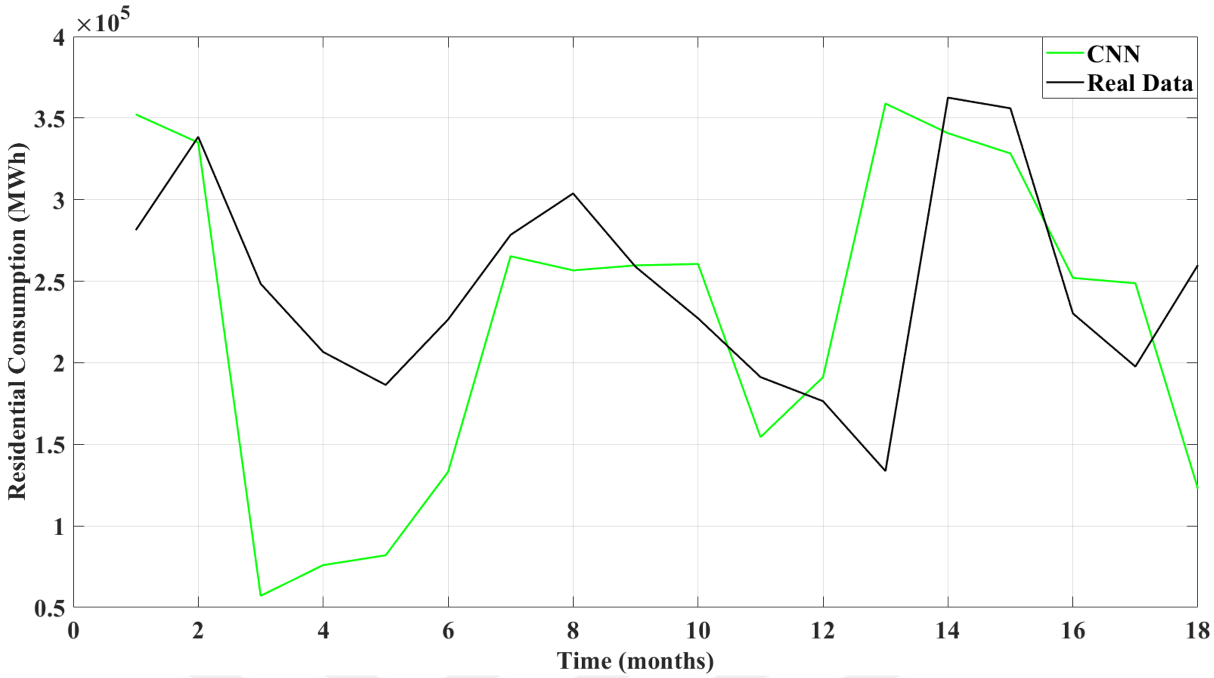
Figure 4.2. Prediction performance of the proposed CNN model over test data for the lighting load in (a) Adana, (b) Mersin, and (c) Antalya provinces.


×10^5
CNN
Real Data
Residential Consumption Load (MWh)
Time (months)

(a)

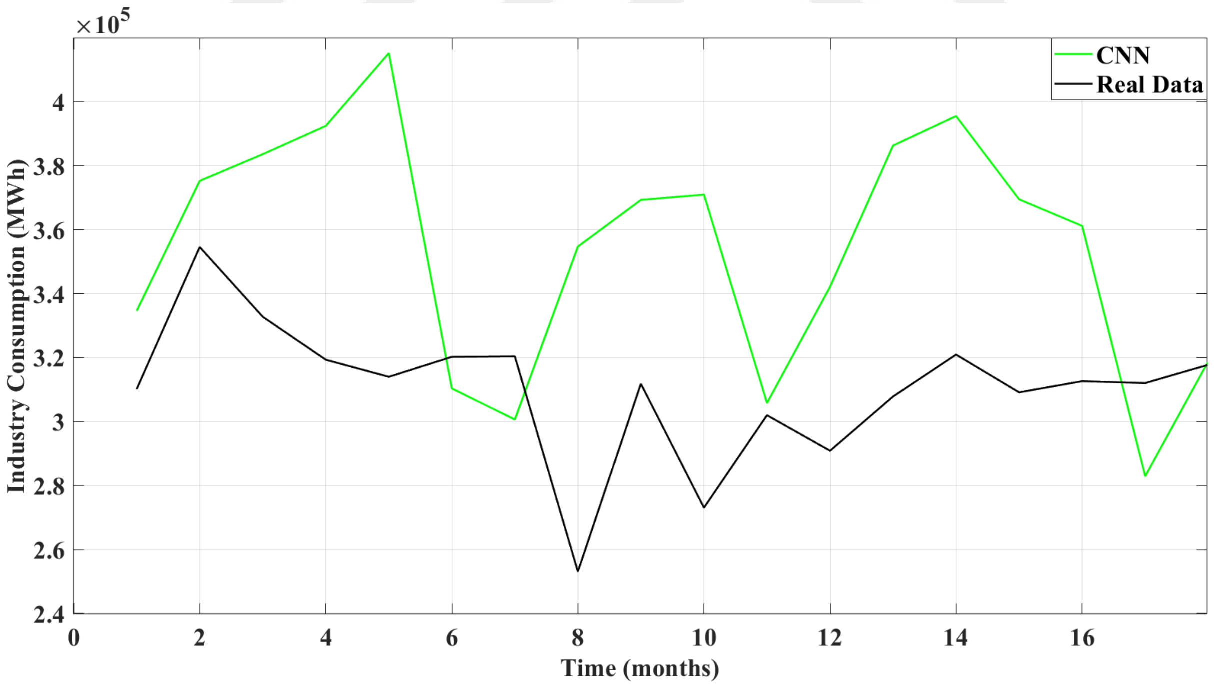

×10^5
CNN
Real Data
Residential Consumption (MWh)
Time (months)

(b)

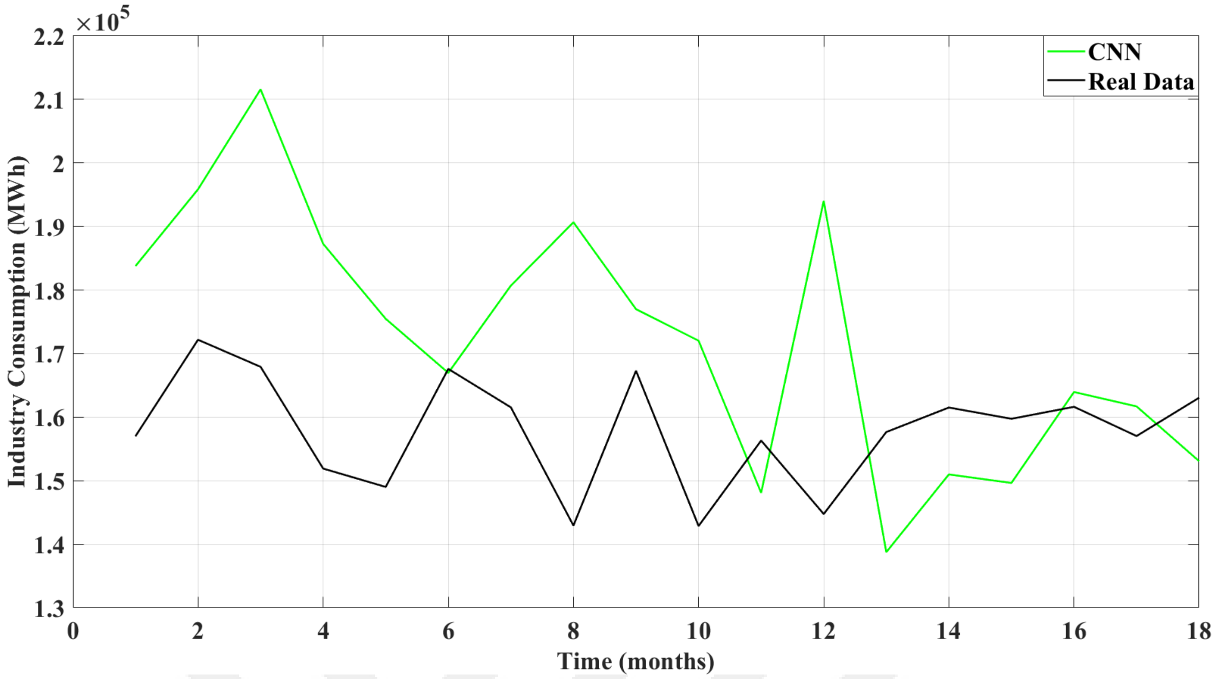


(c)

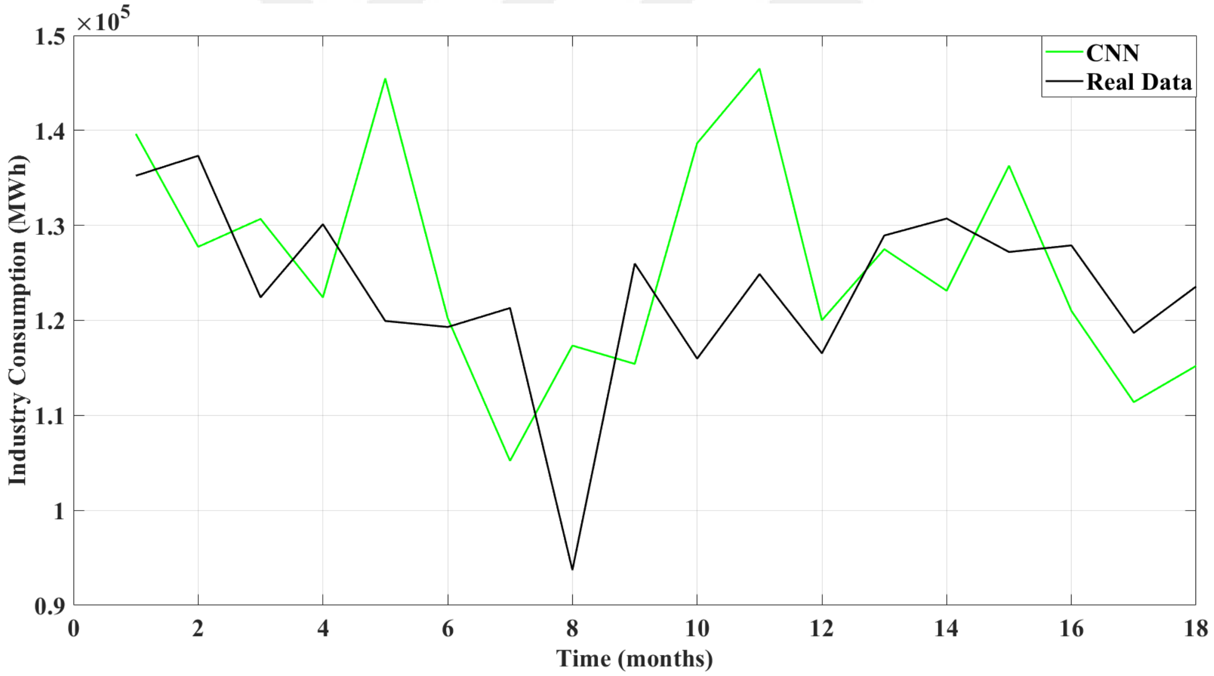
Figure 4.3. Prediction performance of the proposed CNN model over test data for the residential load in (a) Adana, (b) Mersin, and (c) Antalya provinces.



(a)

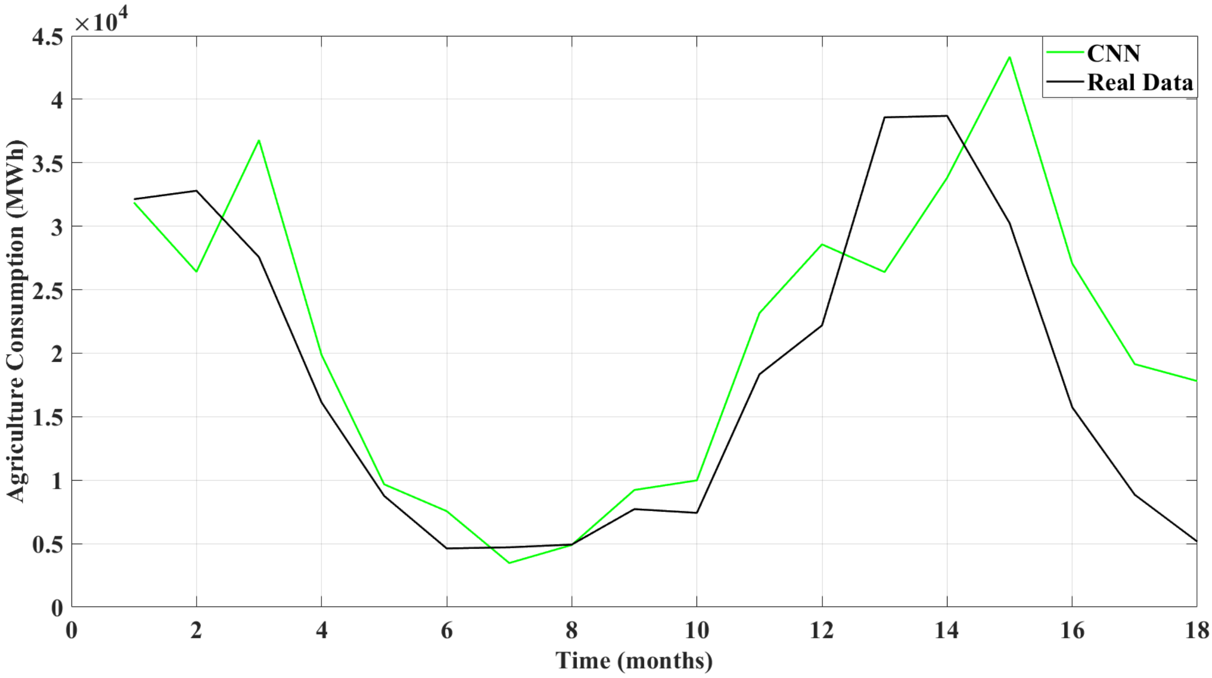


(b)

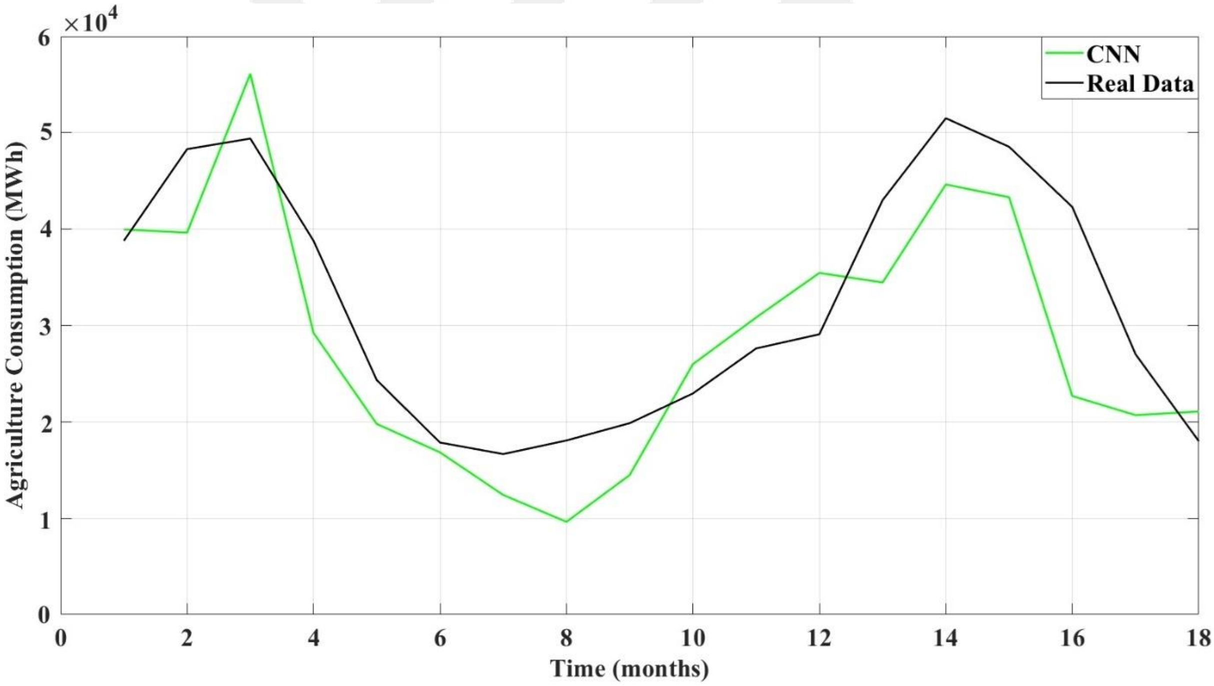


(c)

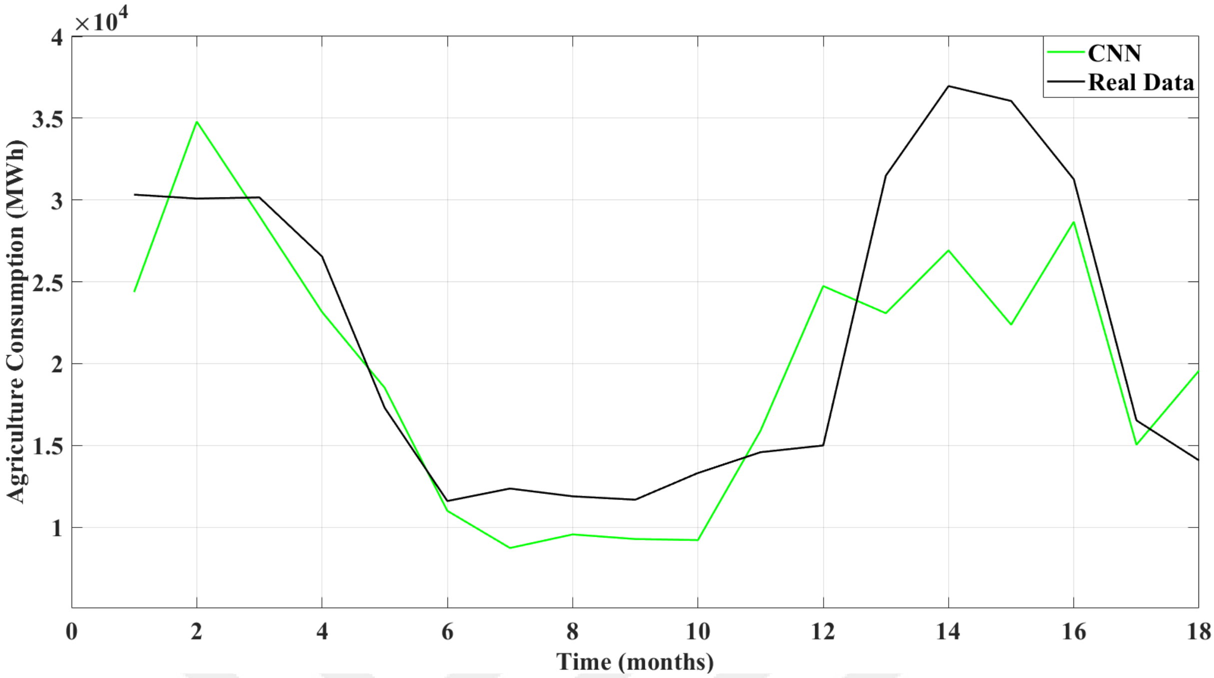
Figure 4.4. Prediction performance of the proposed CNN model over test data for the industry load in (a) Adana, (b) Mersin, and (c) Antalya provinces.


×10^4
4.5
4
3.5
3
2.5
2
1.5
1
0.5
0
Agriculture Consumption (MWh)
0
2
4
6
8
10
12
14
16
18
Time (months)
CNN
Real Data

(a)

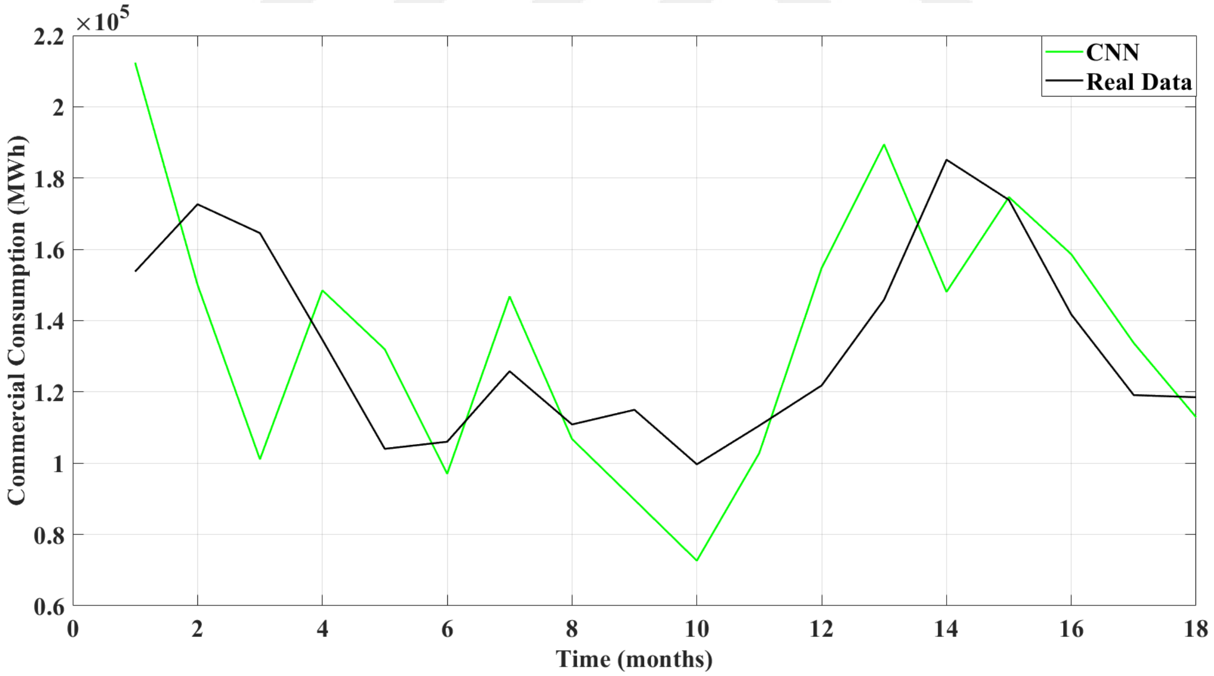

×10^4
6
5
4
3
2
1
0
Agriculture Consumption (MWh)
0
2
4
6
8
10
12
14
16
18
Time (months)
CNN
Real Data

(b)

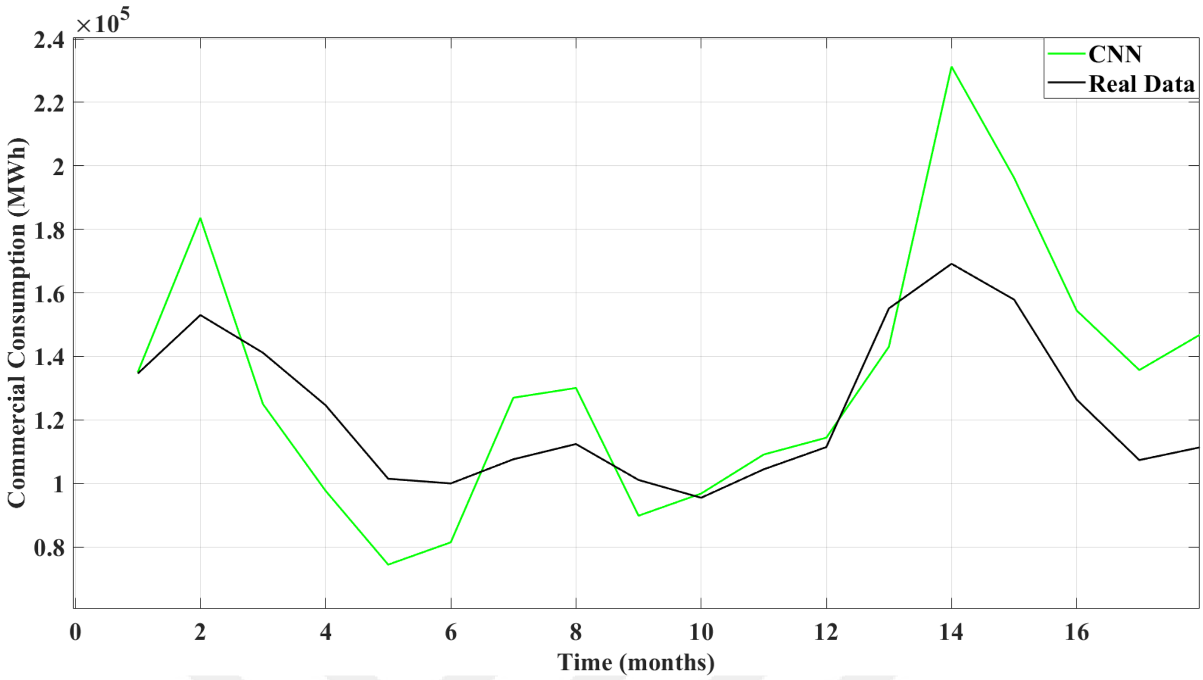


(c)

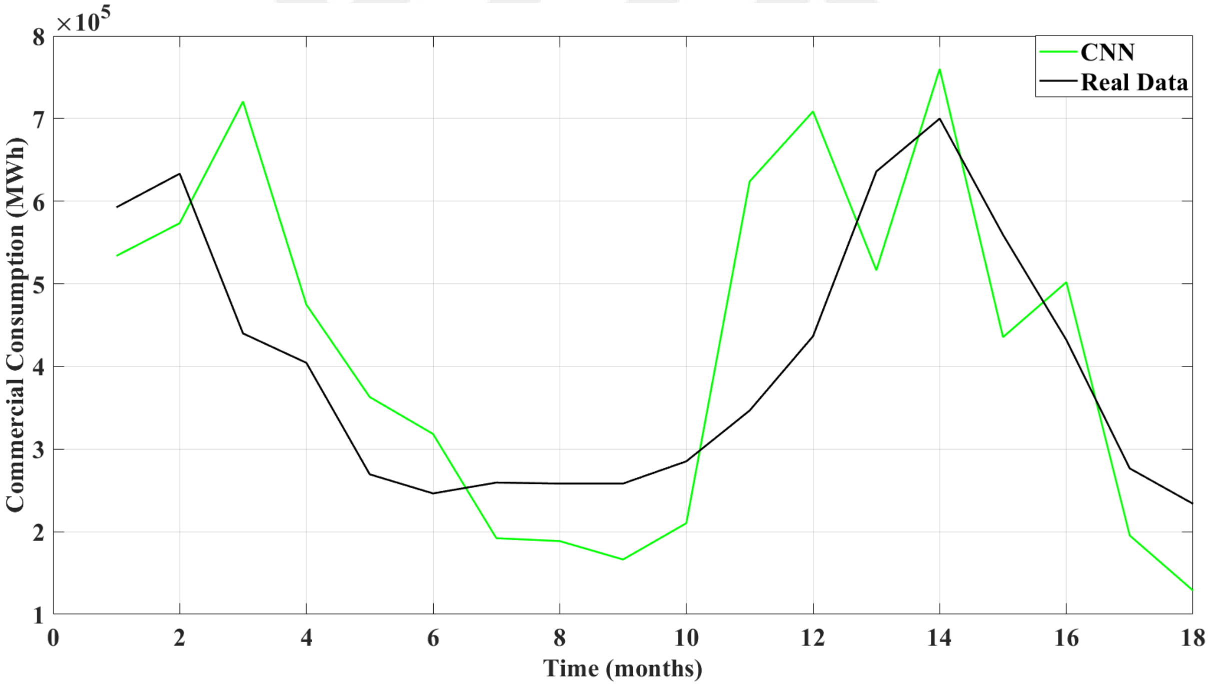
Figure 4.5. Prediction performance of the proposed CNN model over test data for the agriculture load in (a) Adana, (b) Mersin, and (c) Antalya provinces.



(a)

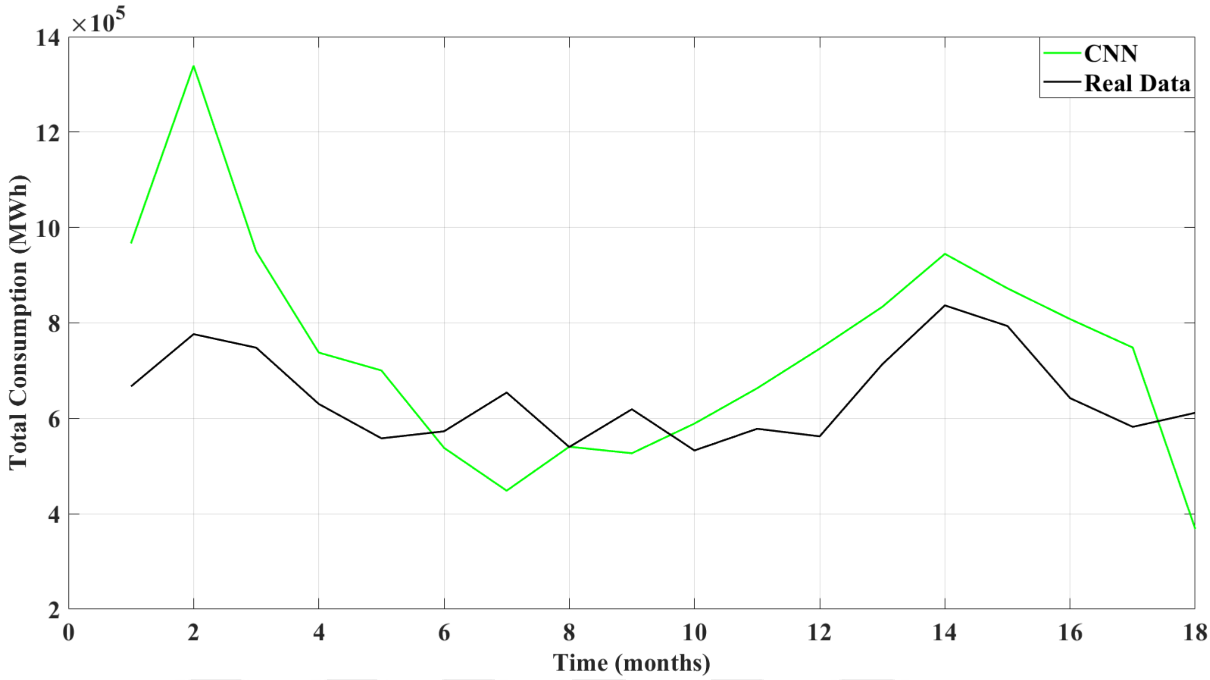


(b)

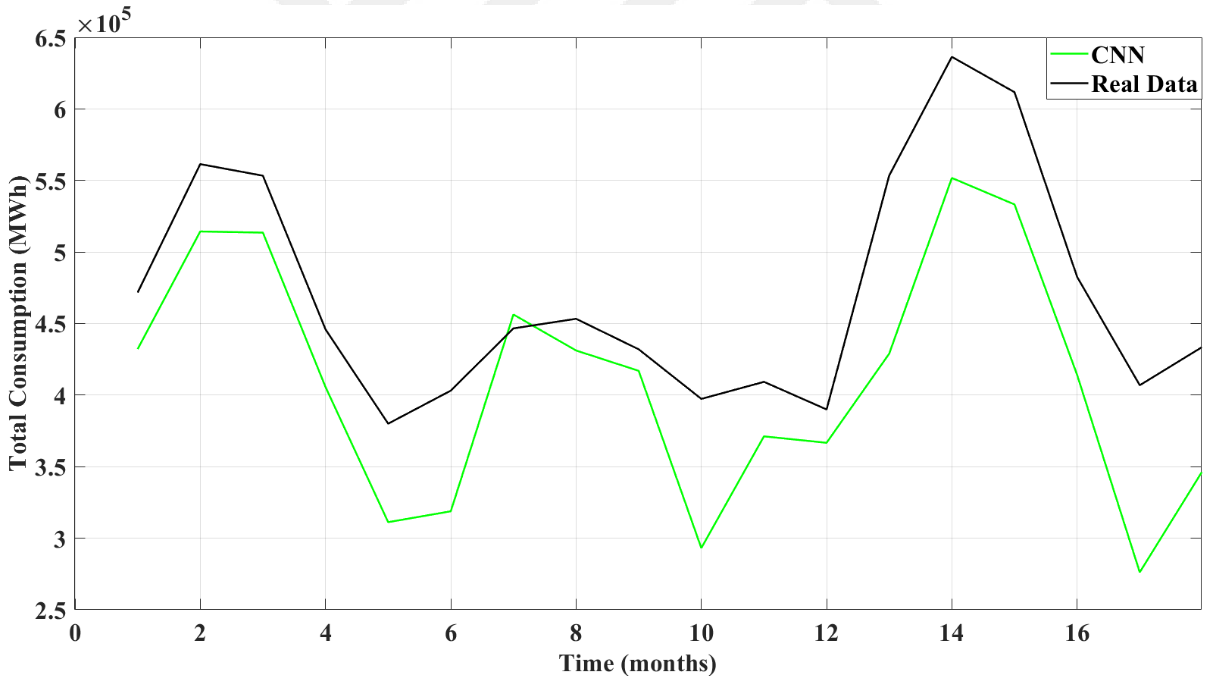


(c)

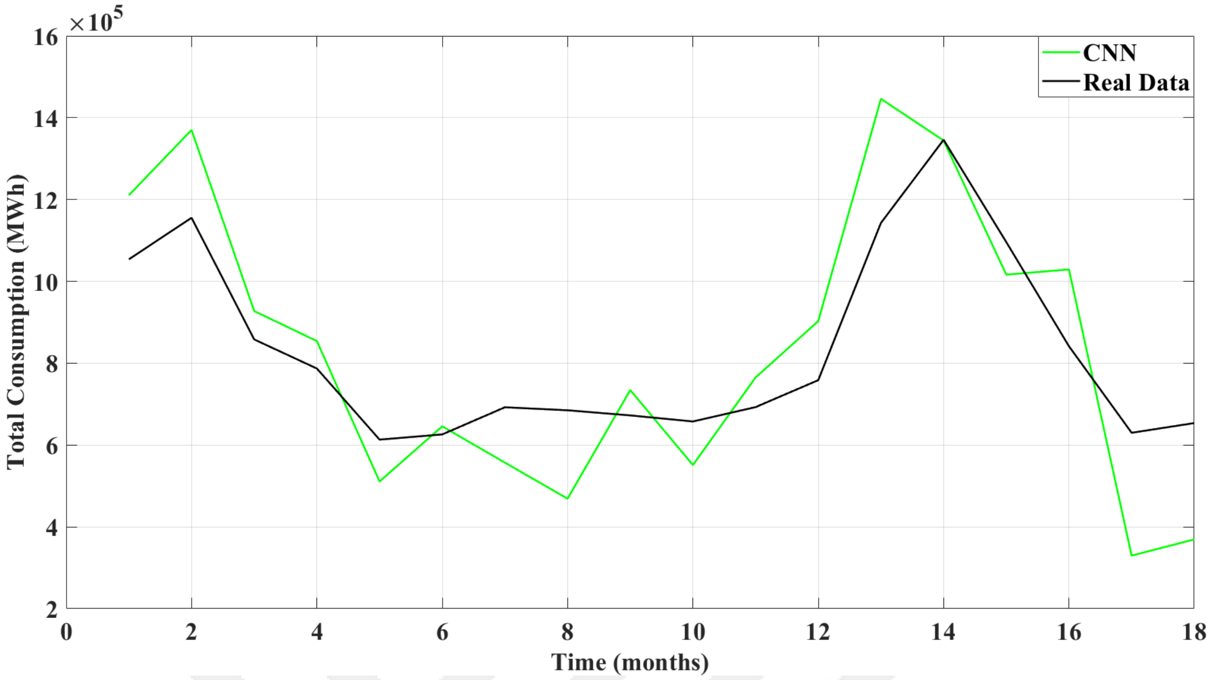
Figure 4.6. Prediction performance of the proposed CNN model over test data for the commercial load in (a) Adana, (b) Mersin, and (c) Antalya provinces.


×10^5
CNN
Real Data
Total Consumption (MWh)
Time (months)

(a)

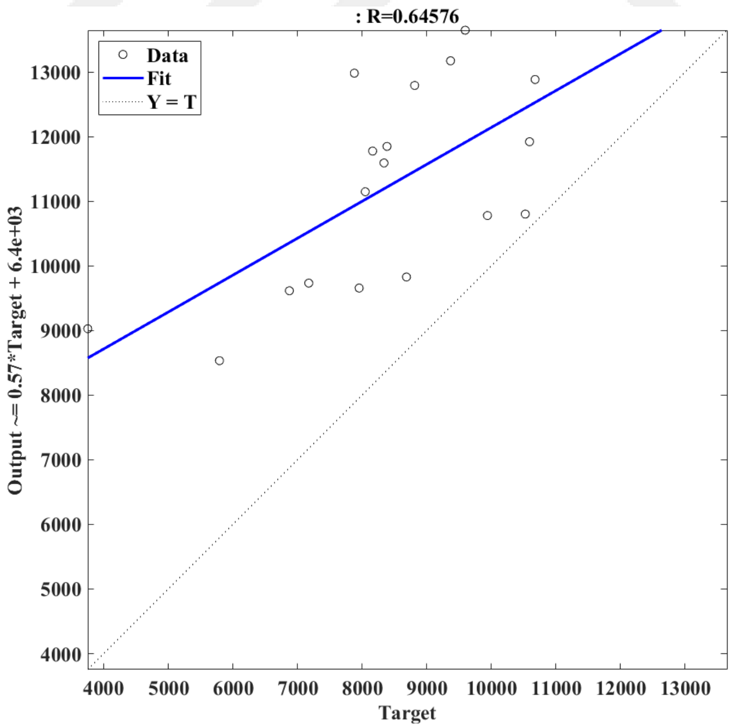

×10^5
CNN
Real Data
Total Consumption (MWh)
Time (months)

(b)

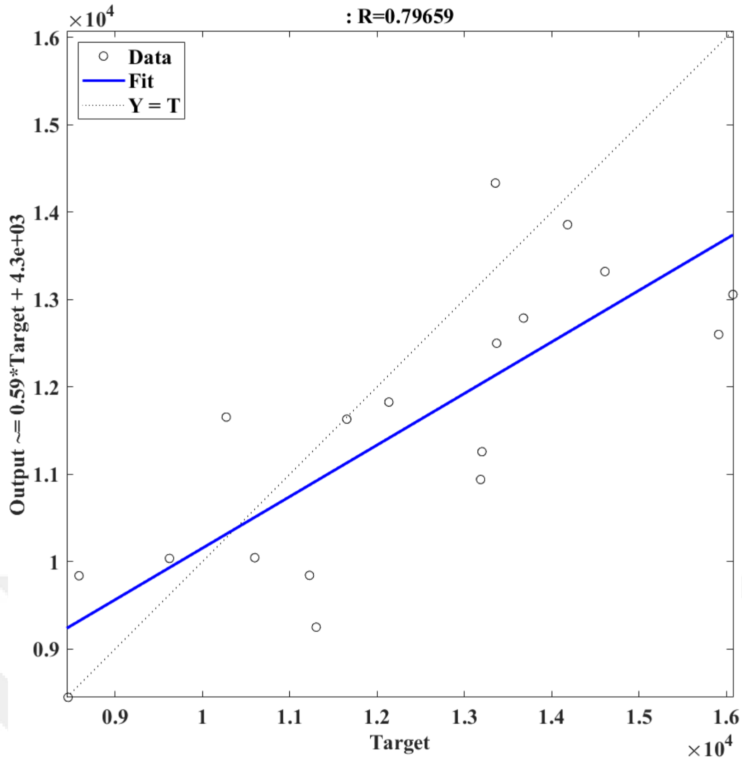


(c)

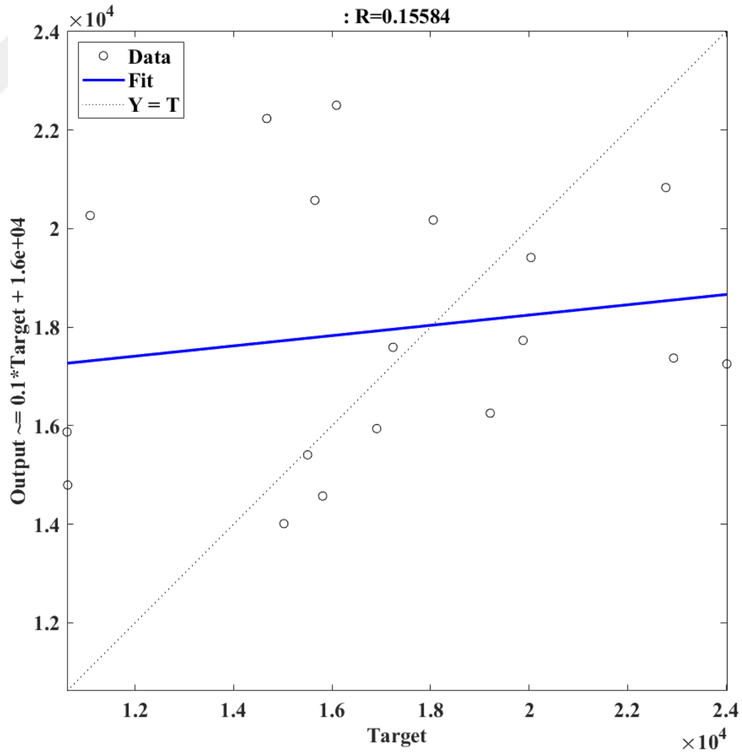
Figure 4.7. Prediction performance of the proposed CNN model over test data for the total load in (a) Adana, (b) Mersin, and (c) Antalya provinces.



(a)

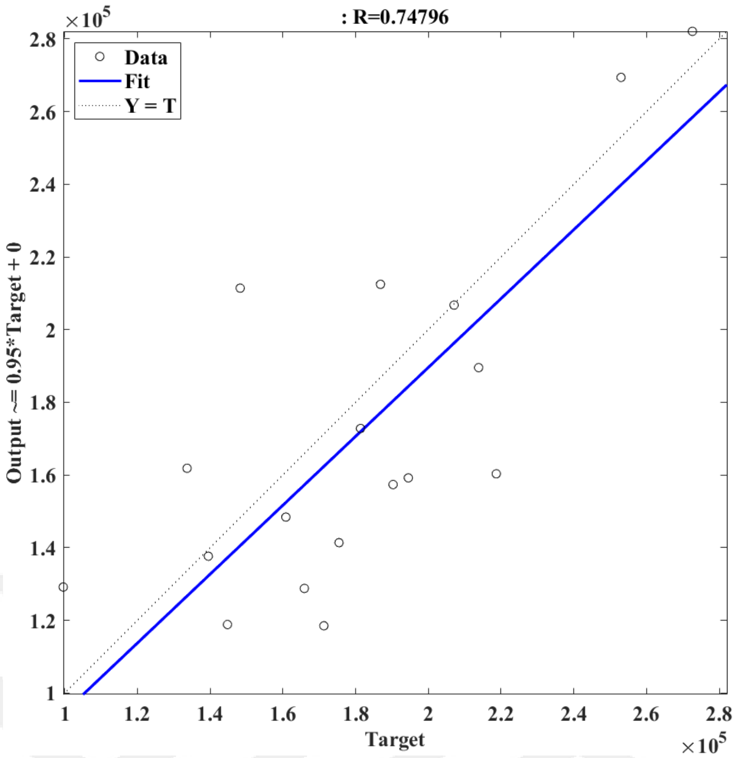


(b)

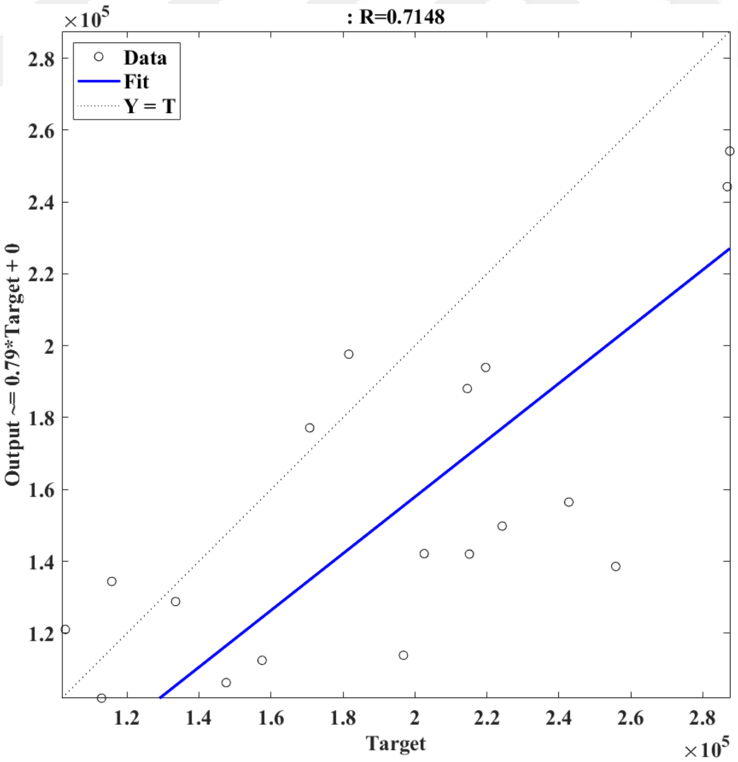


(c)

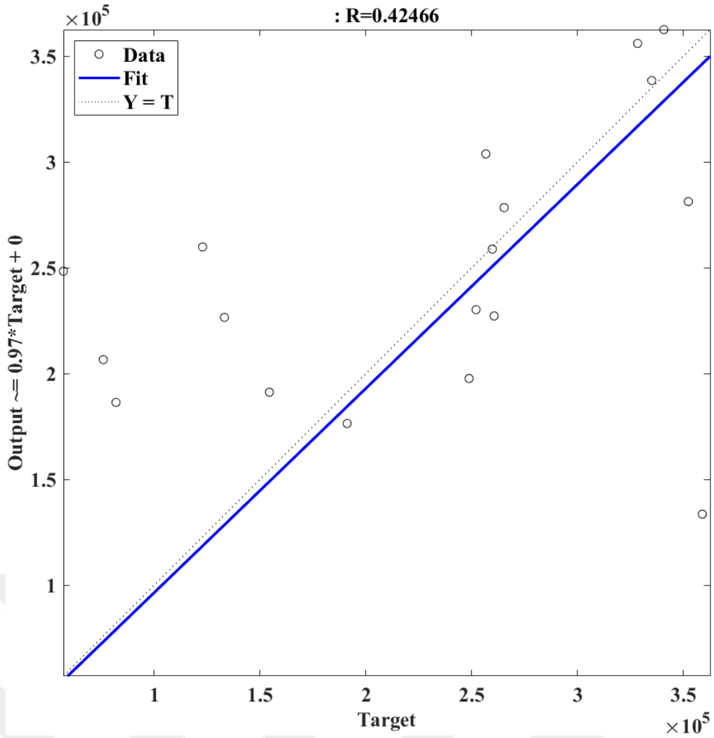
Figure 4.8. Linear regression graphs of the CNN model for the lighting load in (a) Adana, (b) Mersin, and (c) Antalya provinces.


: R=0.74796
Data
Fit
Y = T
Output ~= 0.95*Target + 0
Target
×10^5

(a)

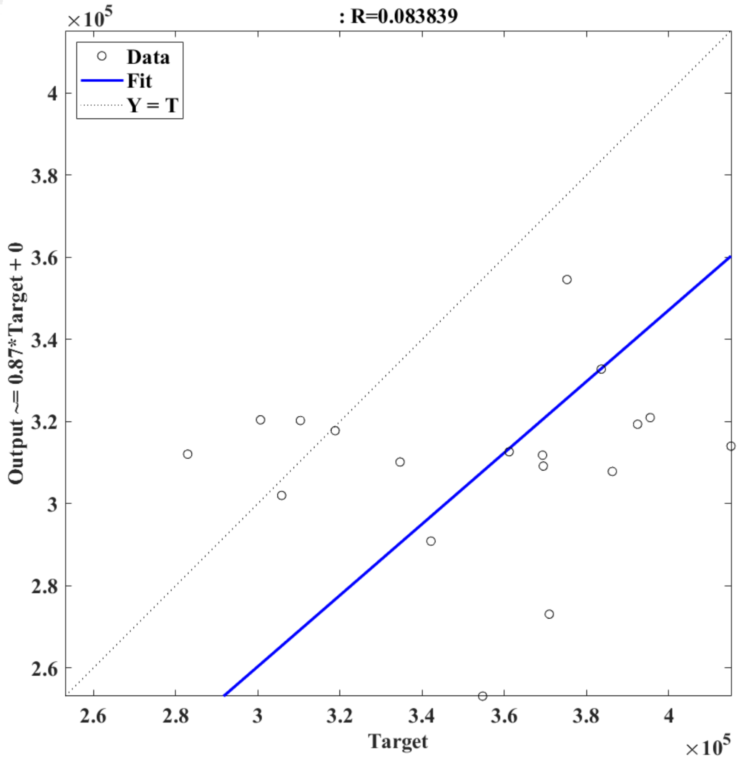

: R=0.7148
Data
Fit
Y = T
Output ~= 0.79*Target + 0
Target
×10^5

(b)

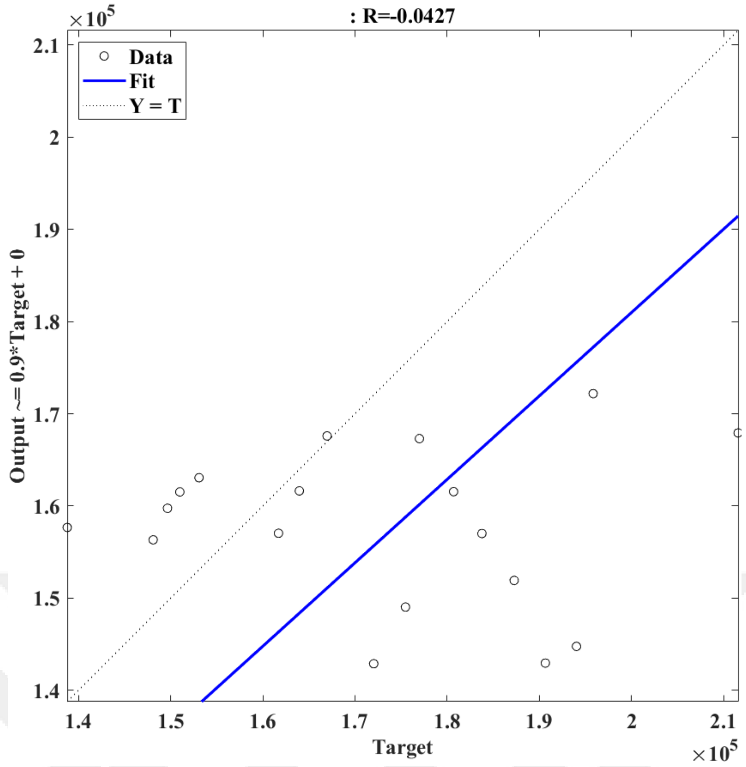


(c)

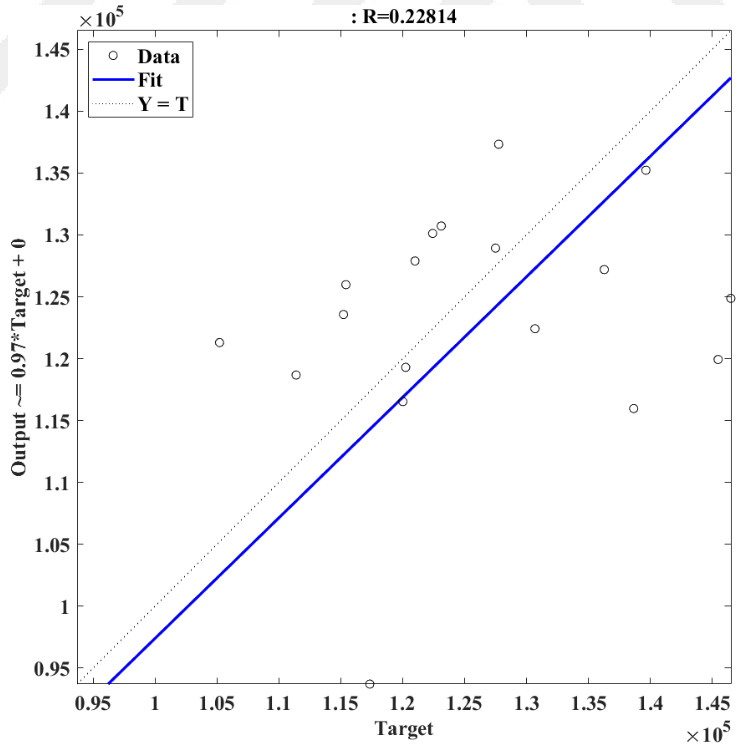
Figure 4.9. Linear regression graphs of the proposed CNN model for the residential load in (a) Adana, (b) Mersin, and (c) Antalya provinces.



(a)

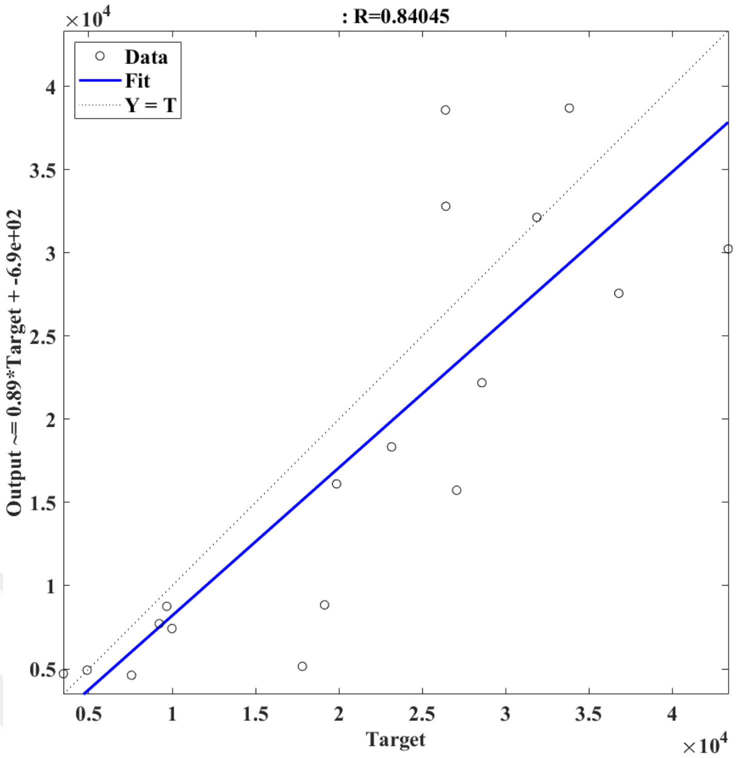


(b)



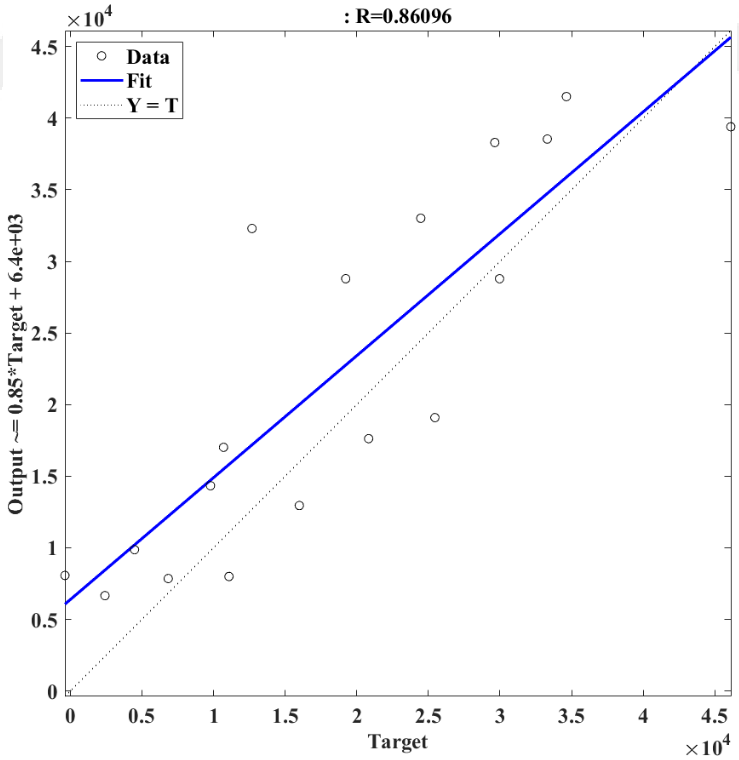
(c)

Figure 4.10. Linear regression graphs of the proposed CNN model for the industry load in (a) Adana, (b) Mersin, and (c) Antalya provinces.



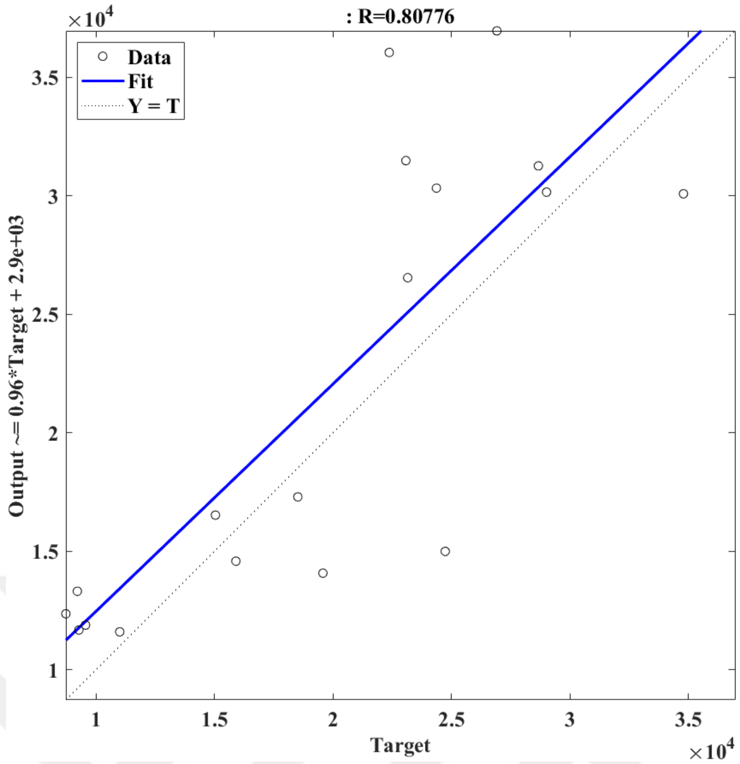
×10^4
: R=0.84045
Data
Fit
Y = T
Output ~= 0.89*Target + -6.9e+02
Target
×10^4

(a)



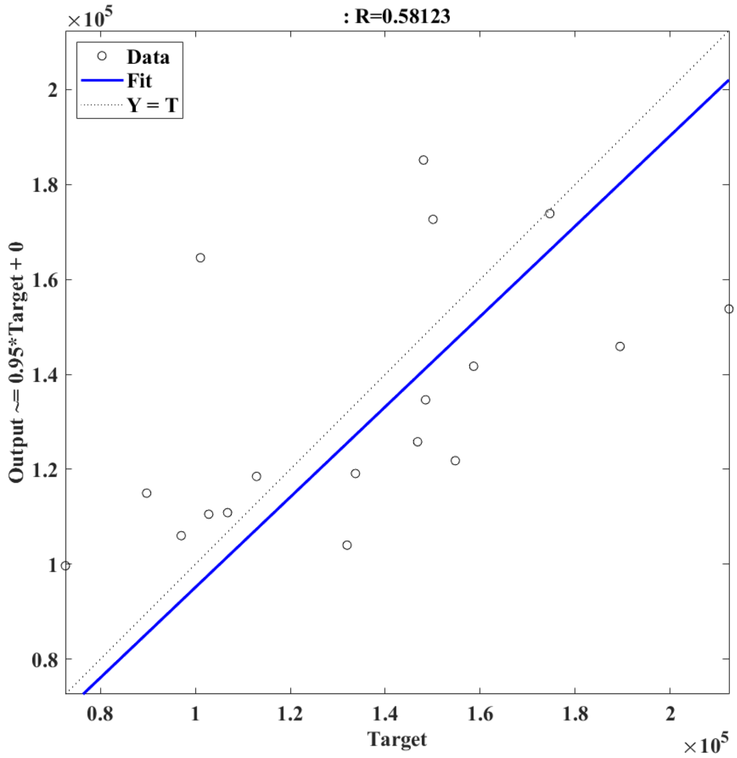
×10^4
: R=0.86096
Data
Fit
Y = T
Output ~= 0.85*Target + 6.4e+03
Target
×10^4

(b)

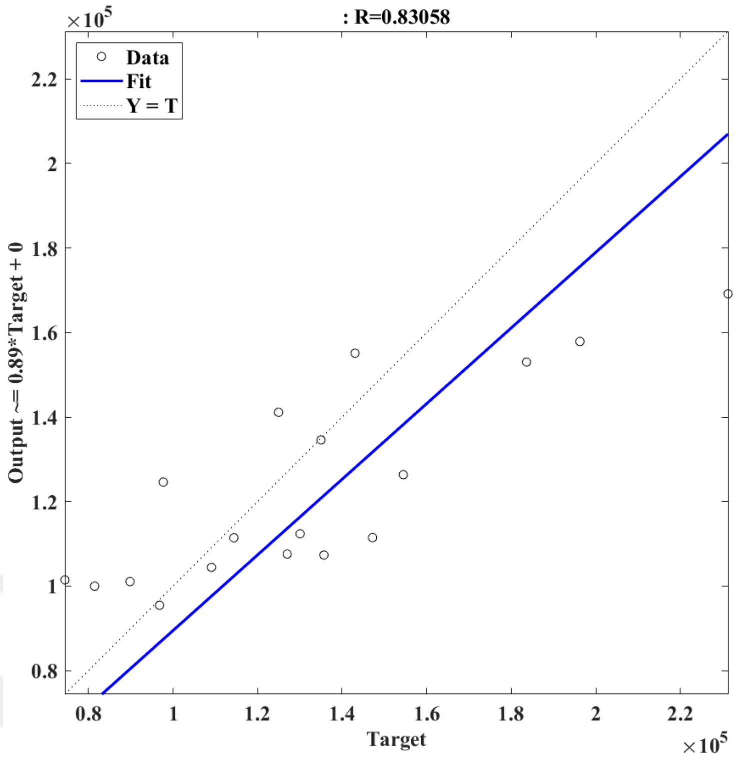


(c)

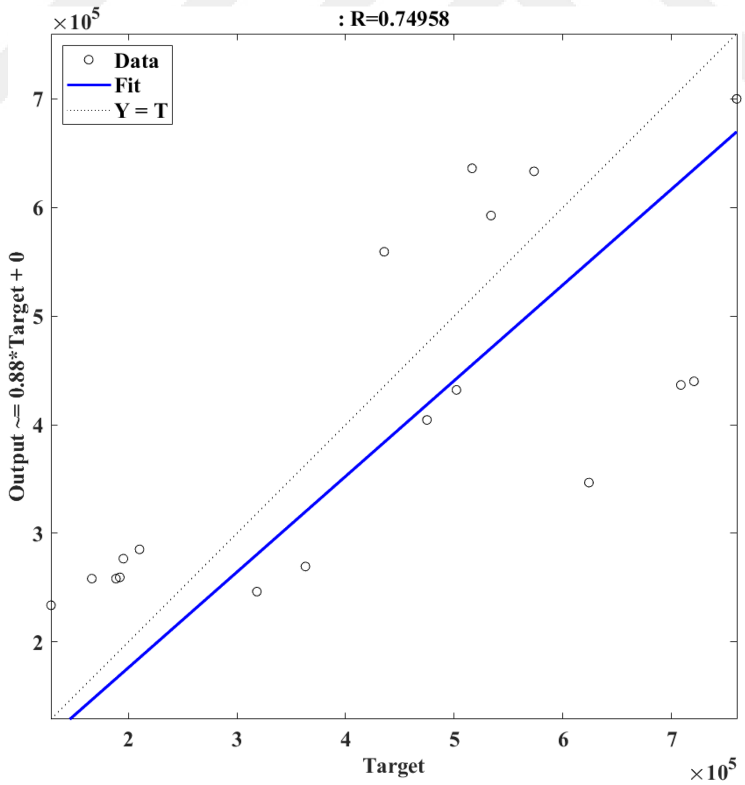
Figure 4.11. Linear regression graphs of the proposed CNN model for the agriculture load in (a) Adana, (b) Mersin, and (c) Antalya provinces.



(a)

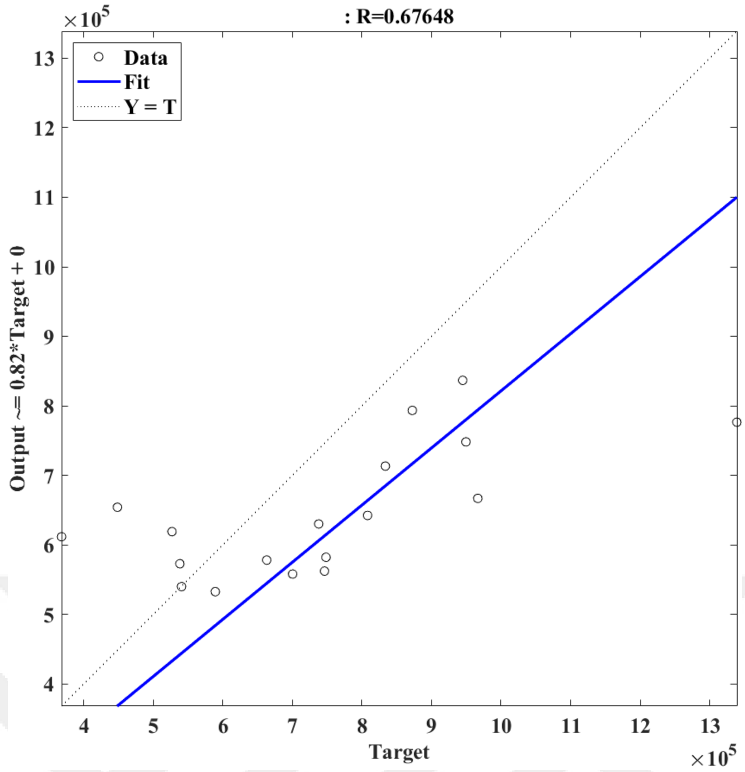


(b)



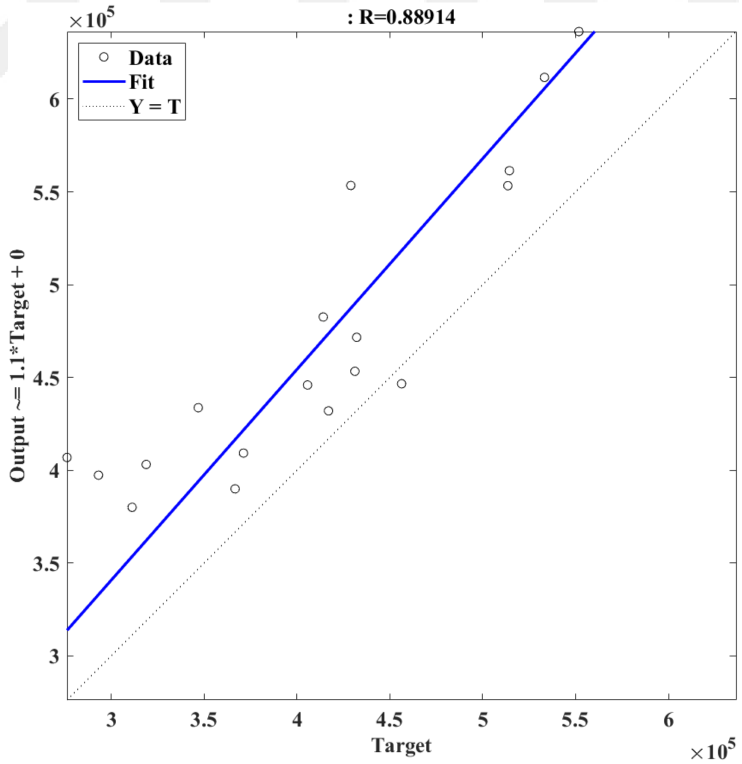
(c)

Figure 4.12. Linear regression graphs of the CNN model for the commercial load in (a) Adana, (b) Mersin, and (c) Antalya provinces.



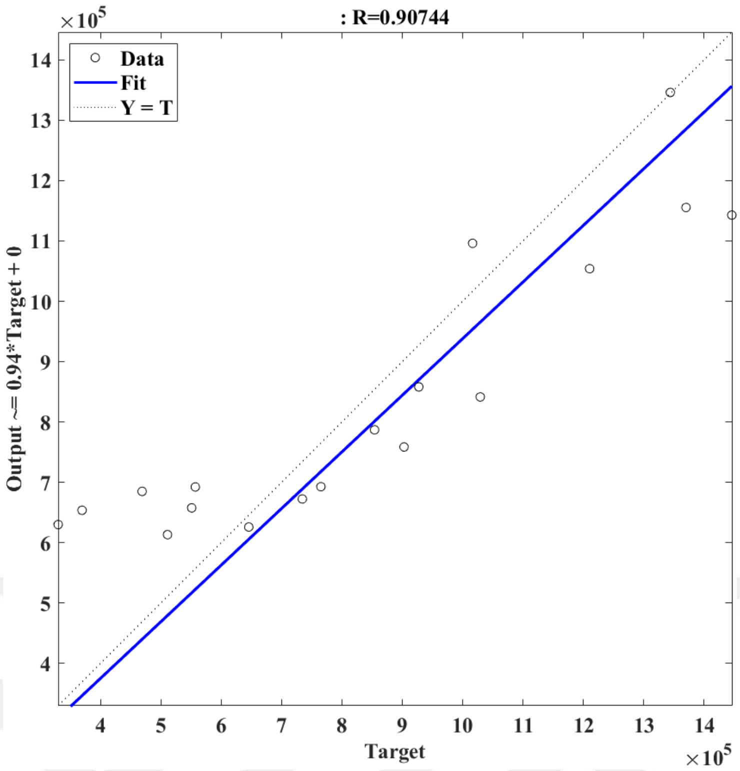
: R=0.67648
×10^5
Data
Fit
Y = T
Output ~= 0.82*Target + 0
Target
×10^5

(a)



: R=0.88914
×10^5
Data
Fit
Y = T
Output ~= 1.1*Target + 0
Target
×10^5

(b)



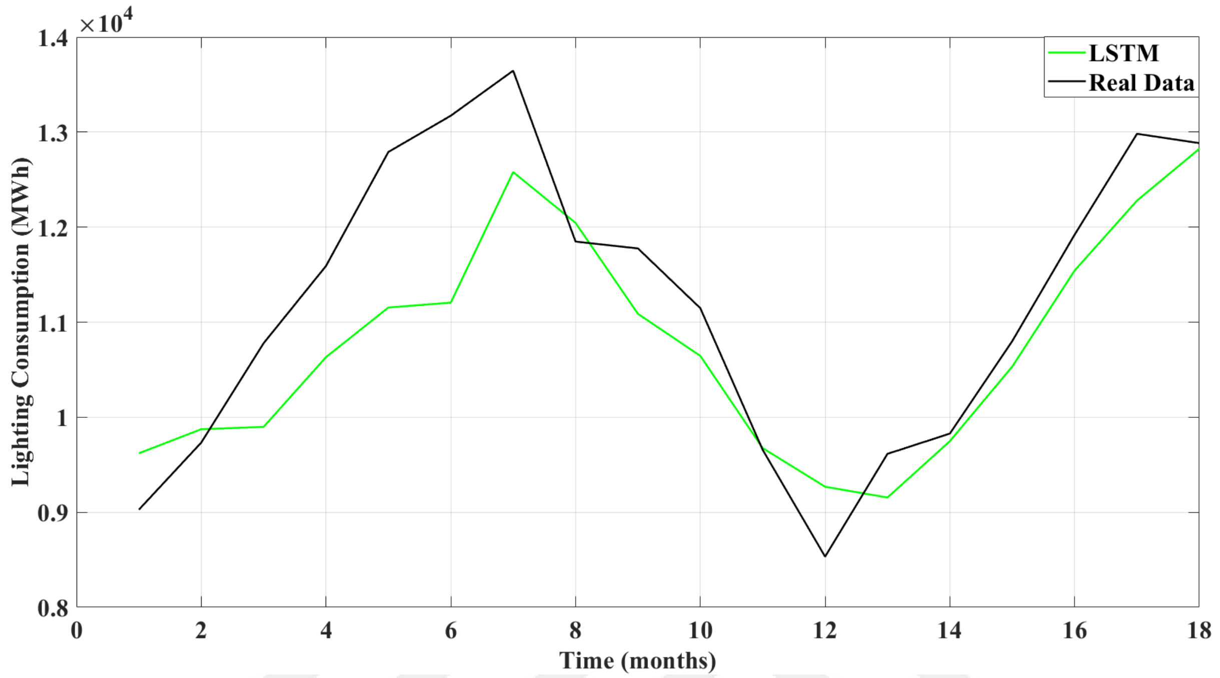
(c)

Figure 4.13. Linear regression graphs of the CNN model for the total load in (a) Adana, (b) Mersin, and (c) Antalya provinces.

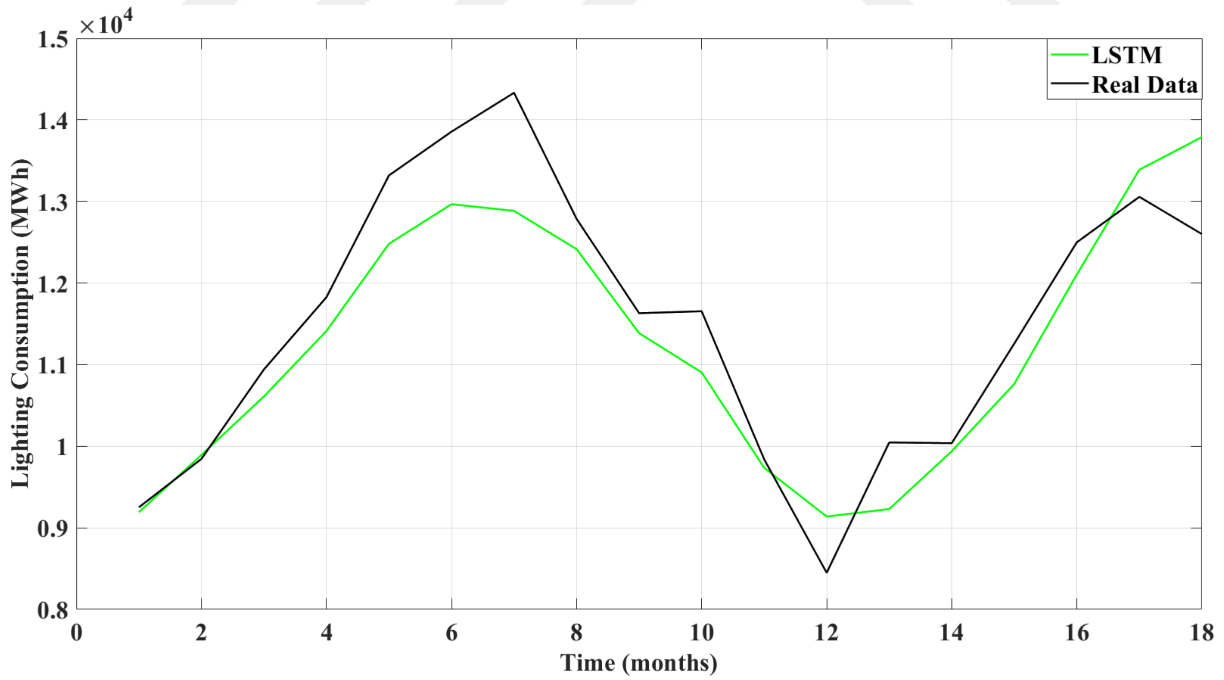
The CNN model used in this study exhibits low accuracy in forecasting electricity loads across different sectors in Adana, Mersin, and Antalya provinces. The model's performance is particularly weak in capturing the variability and dynamics of the actual load data, as evidenced by the significant discrepancies in both the forecast results and linear regression analyses. These findings suggest that further refinement of the model's architecture, training process, and perhaps the inclusion of additional features or more comprehensive training data may be necessary to improve its predictive capabilities.

4.3. The Results of LSTM-Based Electricity Load Forecasting

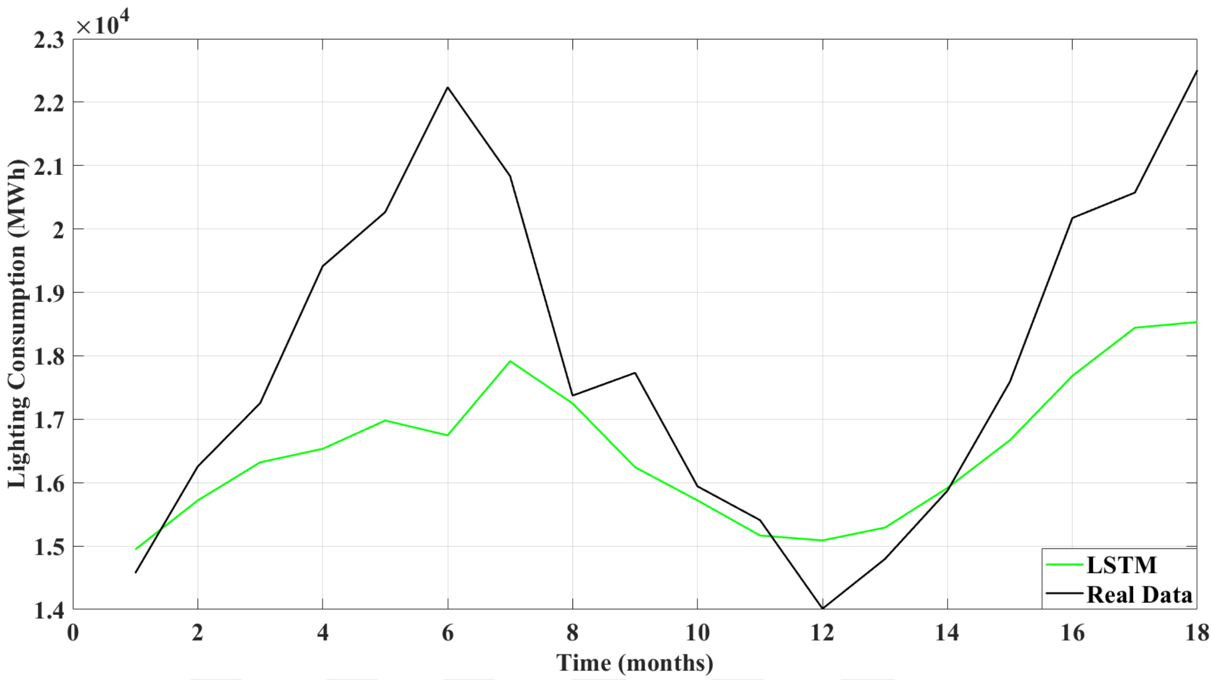
The LSTM model has been employed to predict the electricity load for various sectors in Adana, Mersin, and Antalya. The findings reveal that, compared to the CNN model, the LSTM model produces more accurate and reliable forecasts for different sectors. The prediction performance of the proposed LSTM model over test data for the sectoral electricity load in Adana, Mersin, and Antalya provinces are presented in Figures 4.14-4.19. Figures 4.20-4.25 provide linear regression graphs of the LSTM model for the lighting, residential, industry, agriculture, commercial, and total load, respectively. These graphs plot the predicted load against the actual load, offering a clear visual representation of the model's performance. The regression lines in each figure are close to the ideal line, indicating a high level of predictive accuracy.



(a)

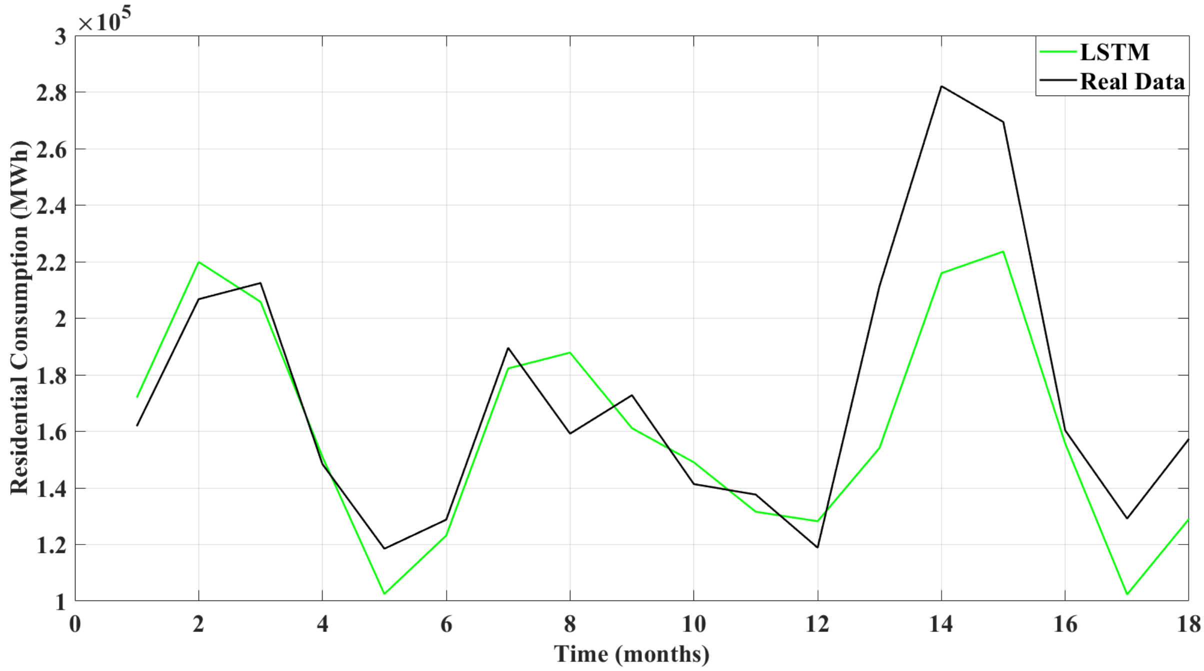


(b)

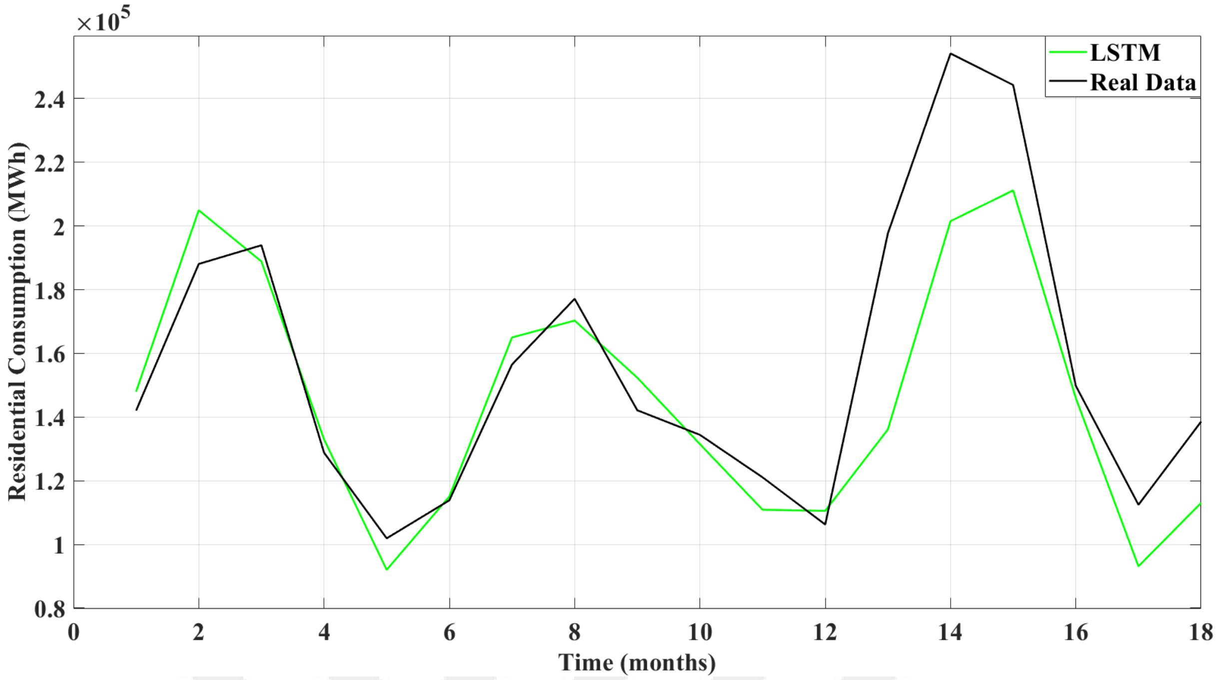


(c)

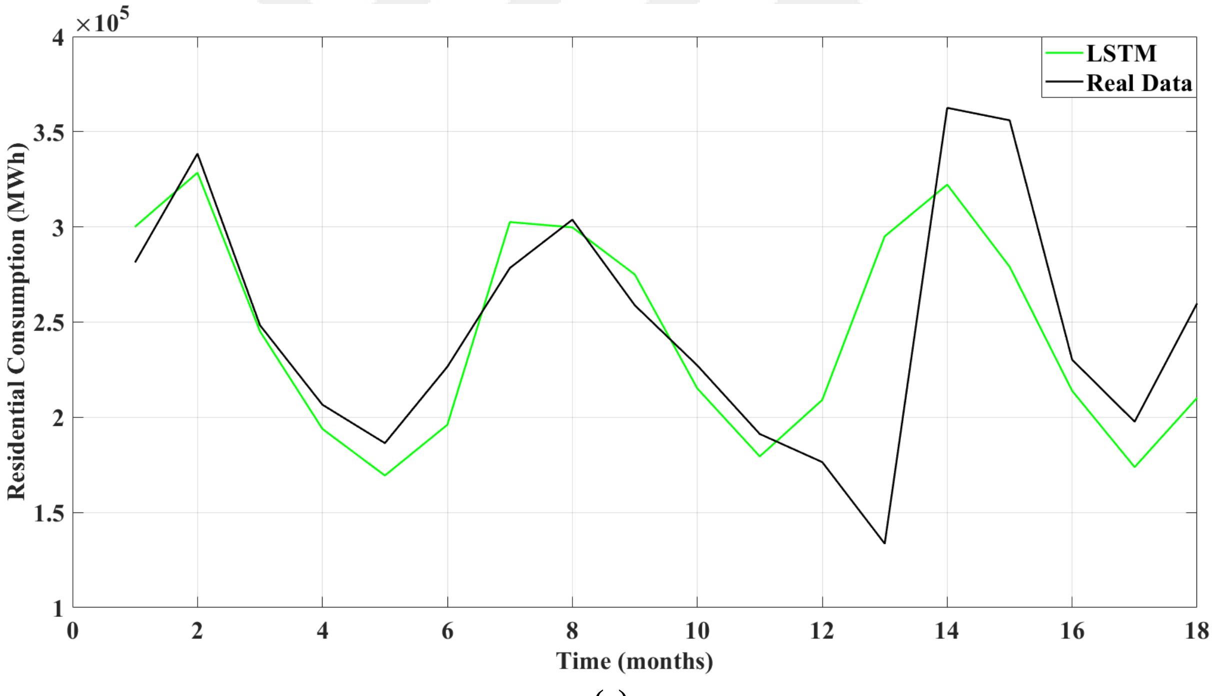
Figure 4.14. Prediction performance of the proposed LSTM model over test data for the lighting load in (a) Adana, (b) Mersin, and (c) Antalya provinces.



(a)

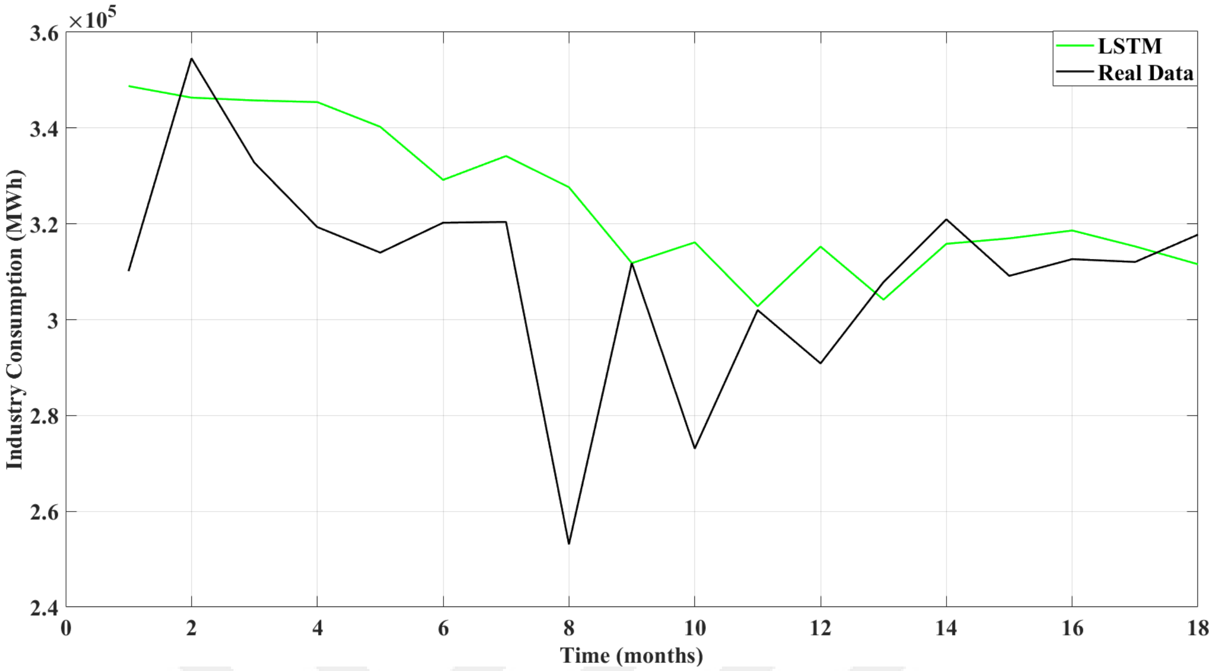


(b)



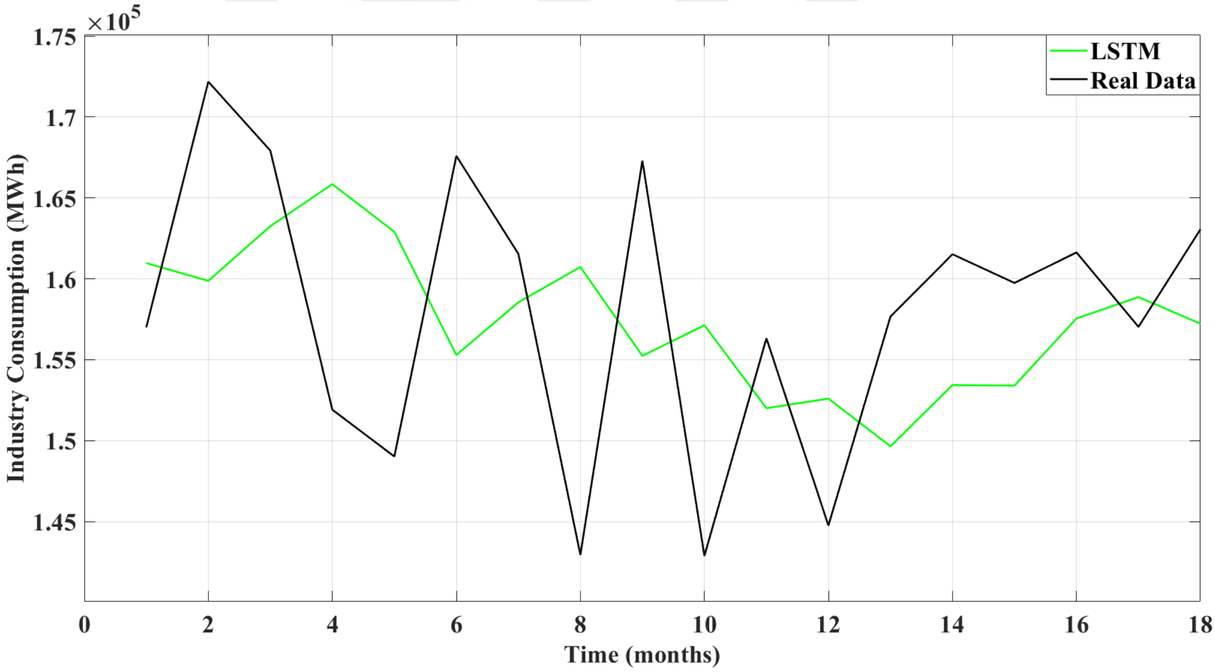
(c)

Figure 4.15. Prediction performance of the proposed LSTM model over test data for the residential load in (a) Adana, (b) Mersin, and (c) Antalya provinces.



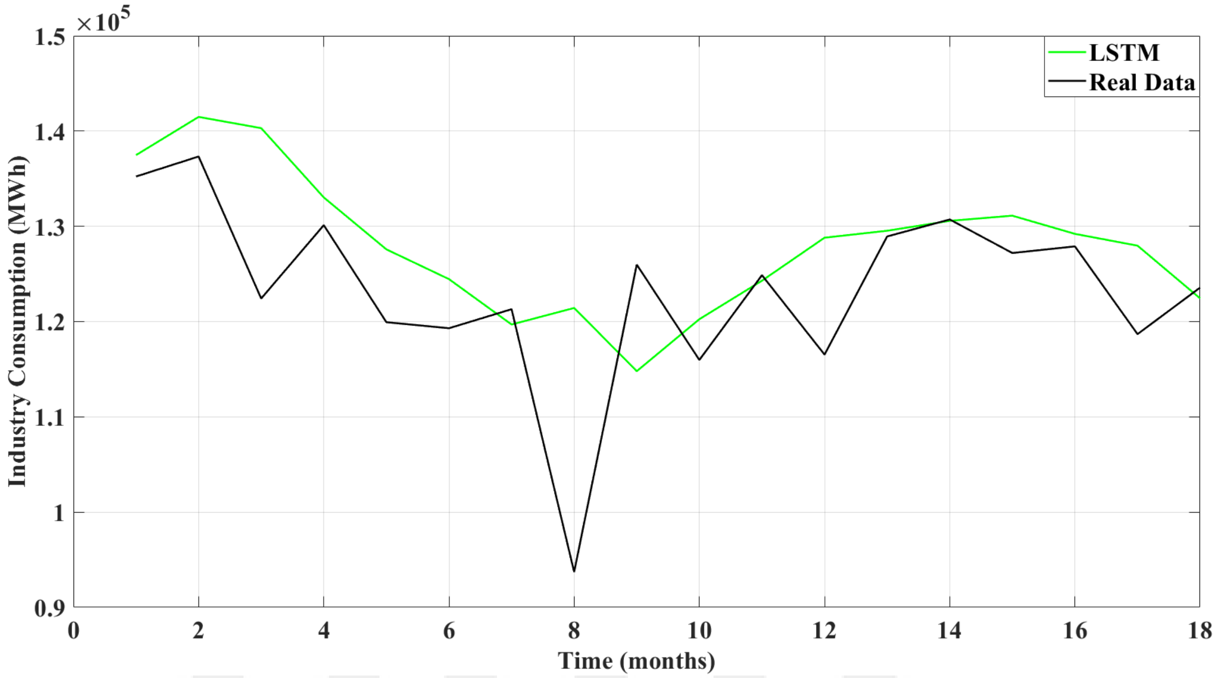
×10^5
3.6
3.4
3.2
3
2.8
2.6
2.4
Industry Consumption (MWh)
0
2
4
6
8
10
12
14
16
18
Time (months)
LSTM
Real Data

(a)



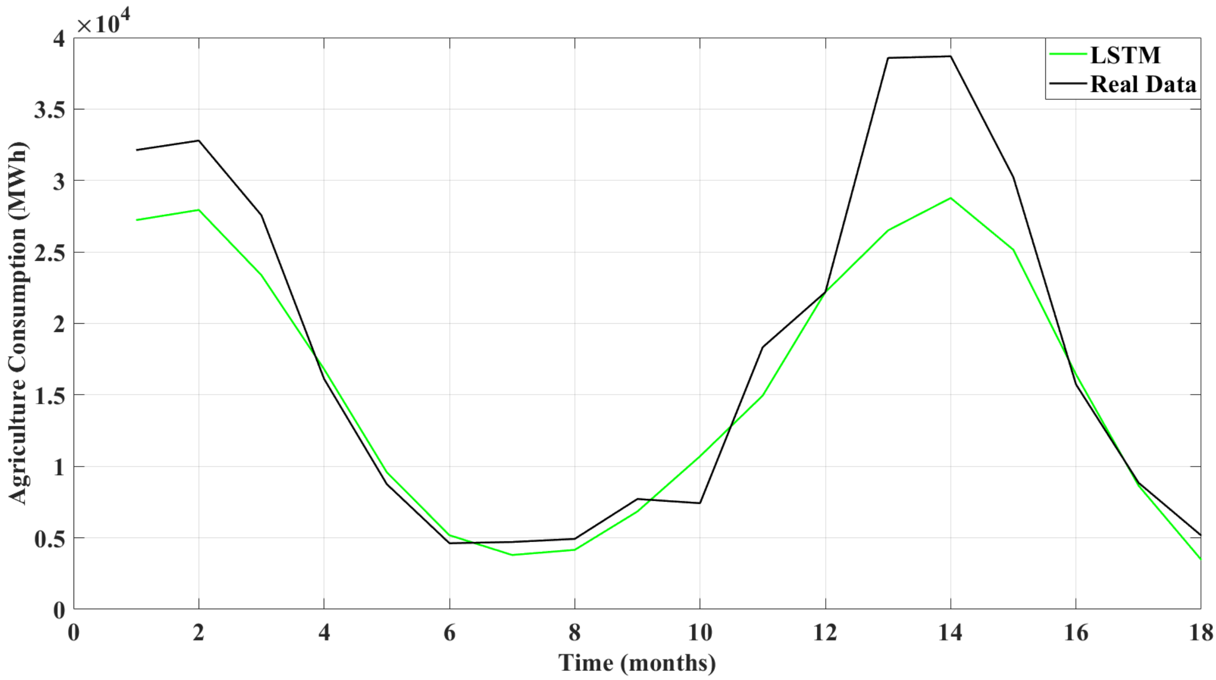
×10^5
1.75
1.7
1.65
1.6
1.55
1.5
1.45
Industry Consumption (MWh)
0
2
4
6
8
10
12
14
16
18
Time (months)
LSTM
Real Data

(b)

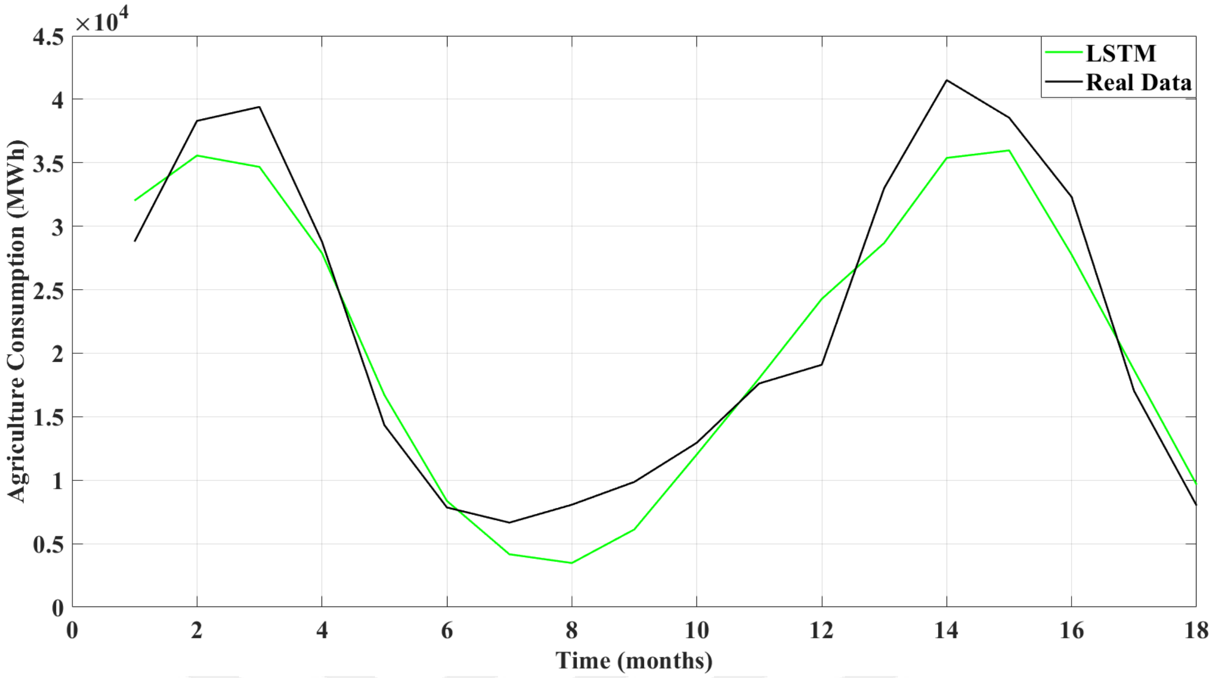


(c)

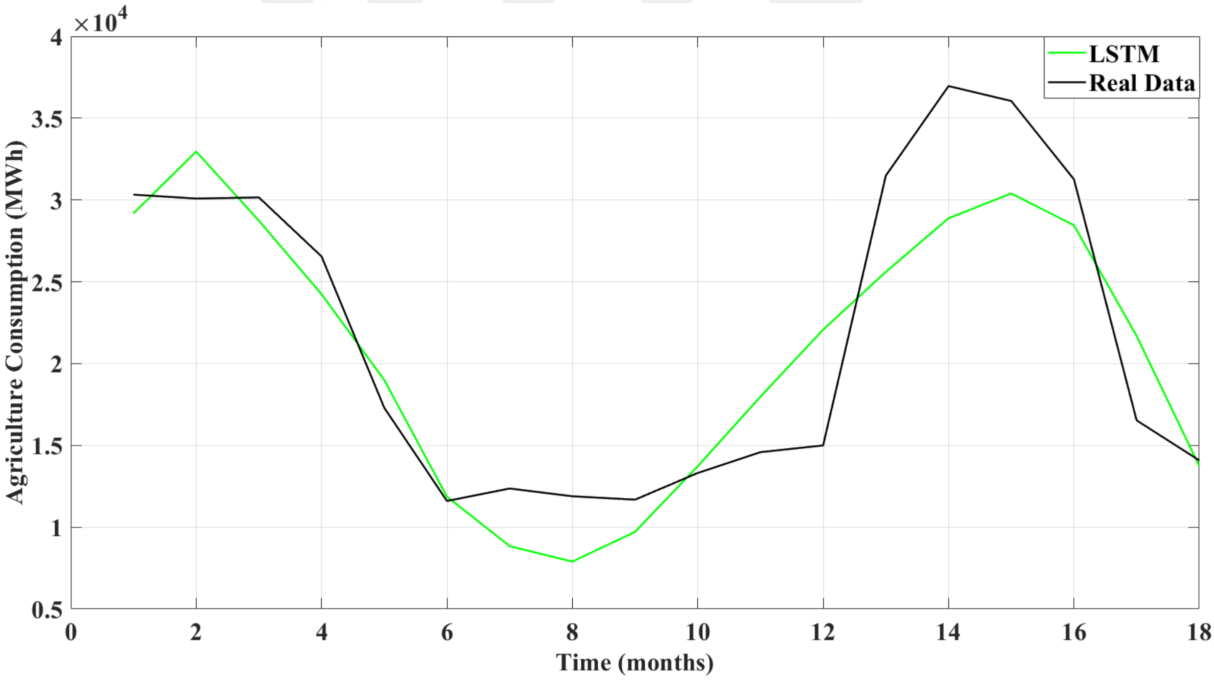
Figure 4.16. Prediction performance of the proposed LSTM model over test data for the industry load in (a) Adana, (b) Mersin, and (c) Antalya provinces.



(a)

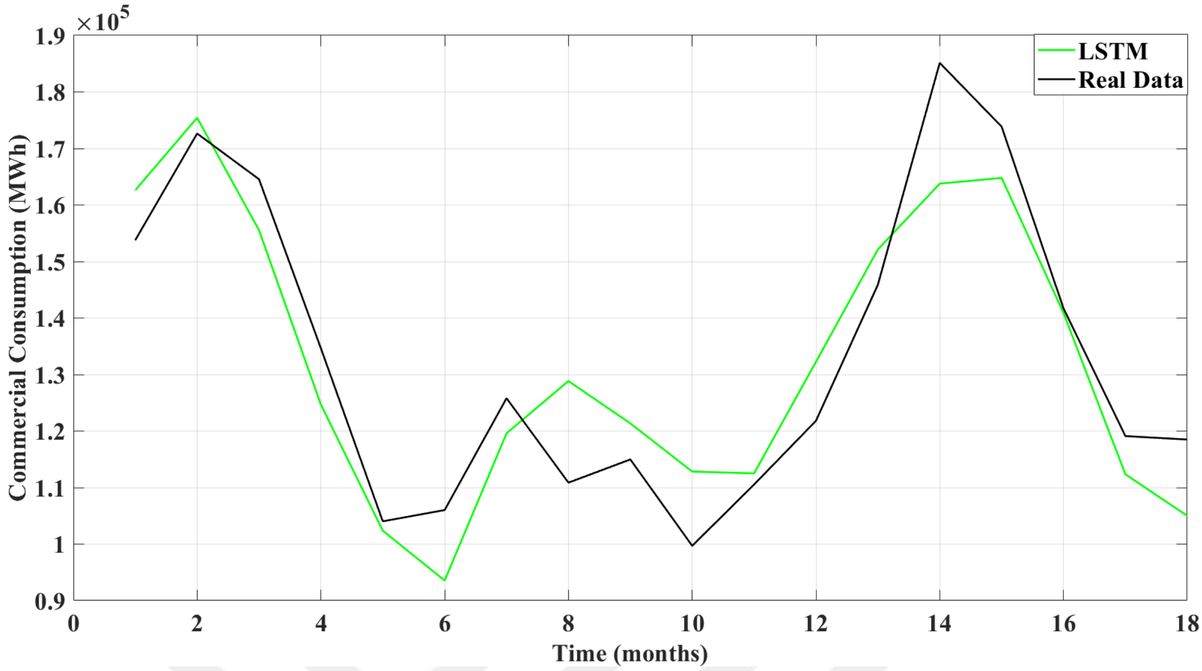


(b)



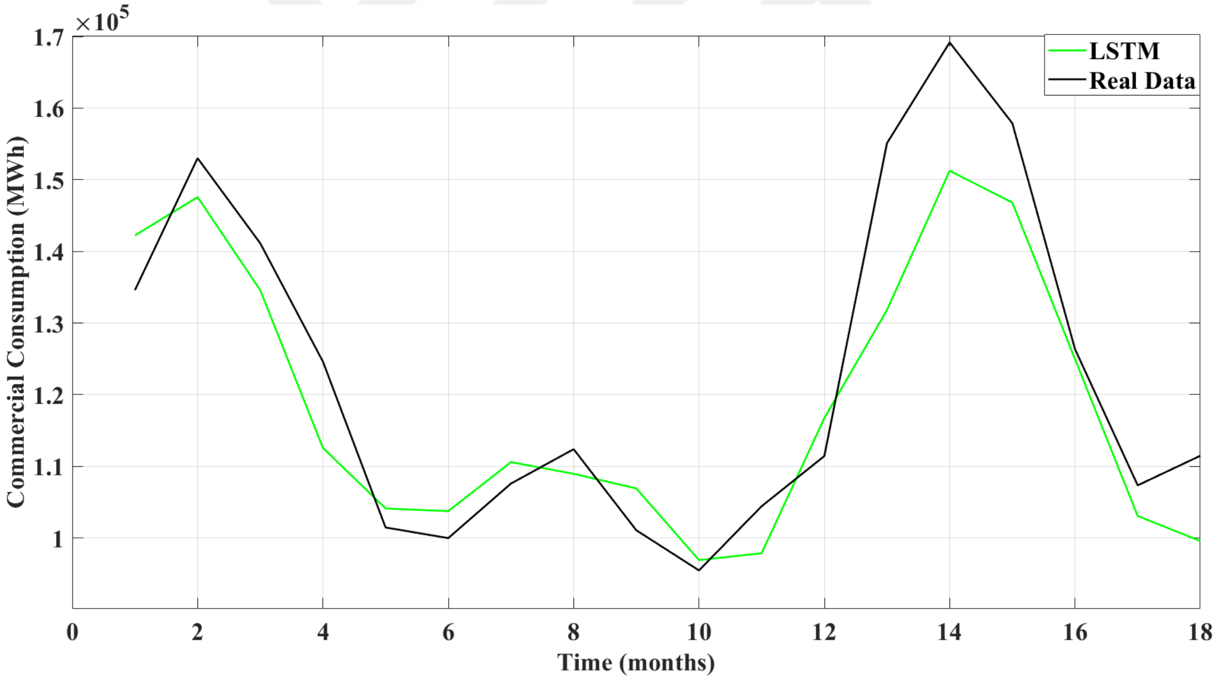
(c)

Figure 4.17. Prediction performance of the proposed LSTM model over test data for the agriculture load in (a) Adana, (b) Mersin, and (c) Antalya provinces.



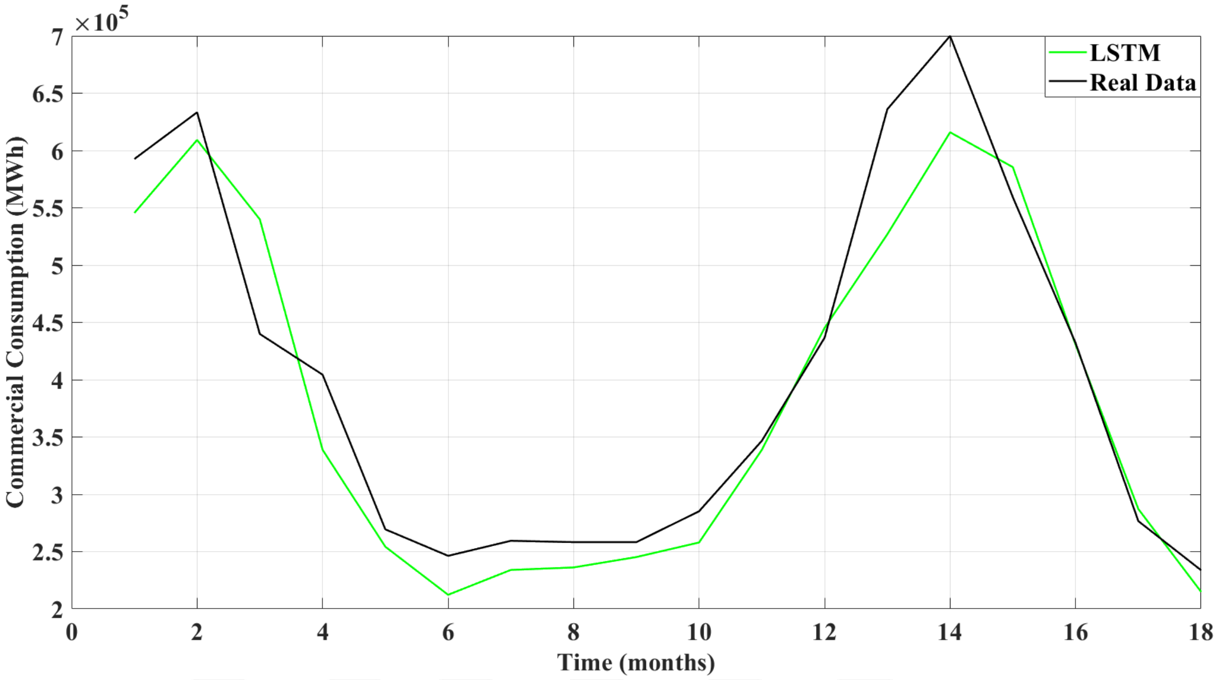
×10^5
1.9
1.8
1.7
1.6
1.5
1.4
1.3
1.2
1.1
1
0.9
Commercial Consumption (MWh)
0
2
4
6
8
10
12
14
16
18
Time (months)
LSTM
Real Data

(a)



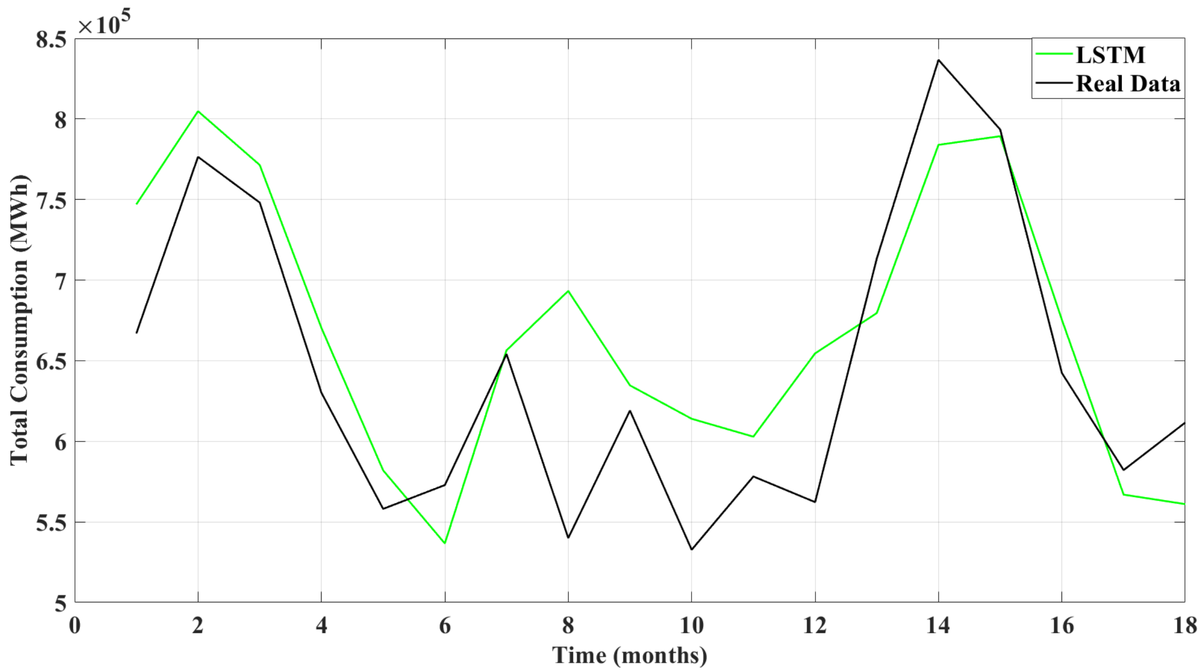
×10^5
1.7
1.6
1.5
1.4
1.3
1.2
1.1
1
Commercial Consumption (MWh)
0
2
4
6
8
10
12
14
16
18
Time (months)
LSTM
Real Data

(b)

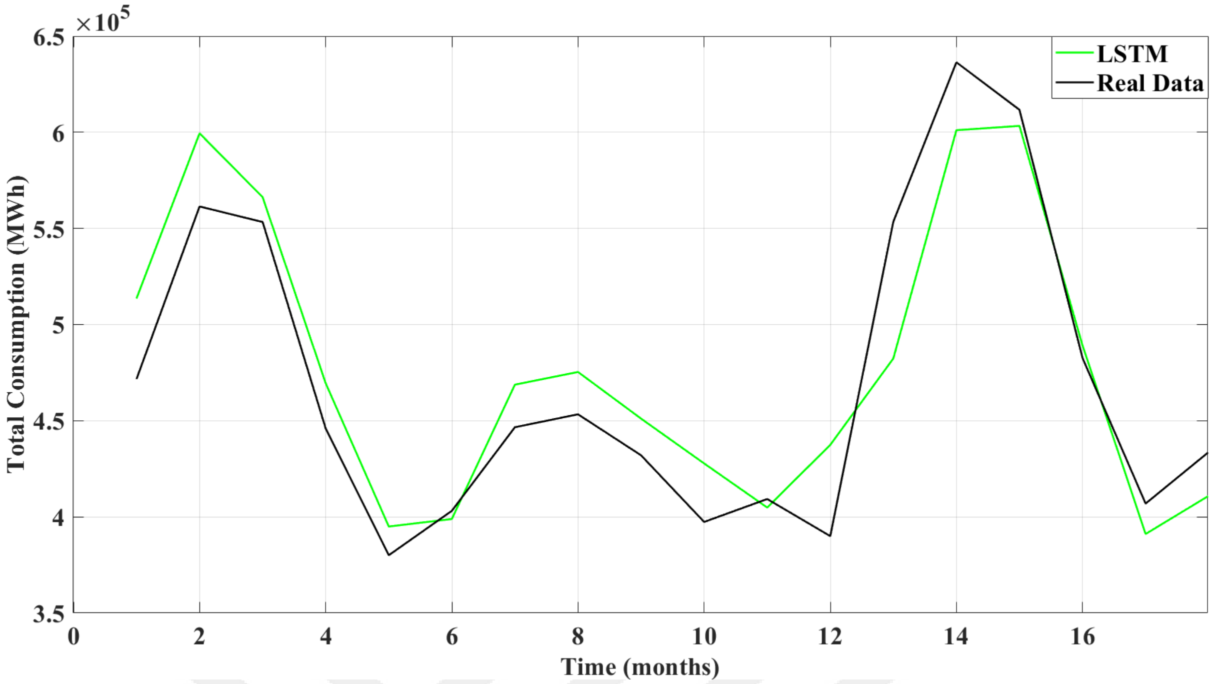


(c)

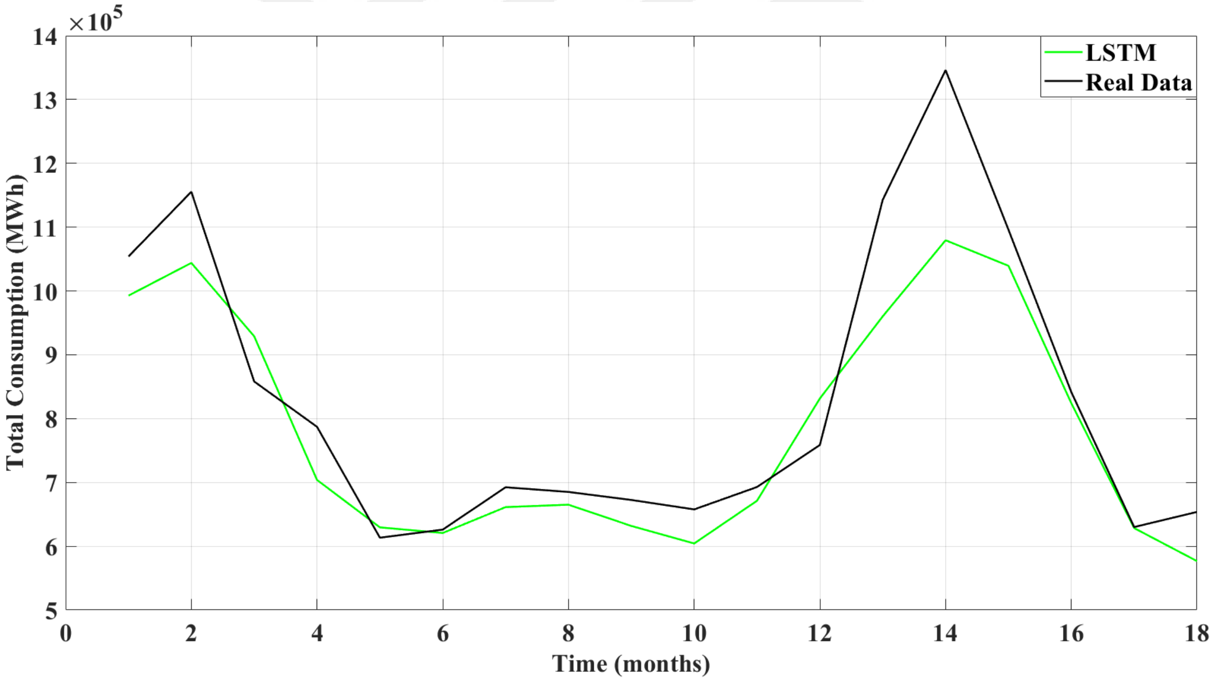
Figure 4.18. Prediction performance of the proposed LSTM model over test data for the commercial load in (a) Adana, (b) Mersin, and (c) Antalya provinces.



(a)

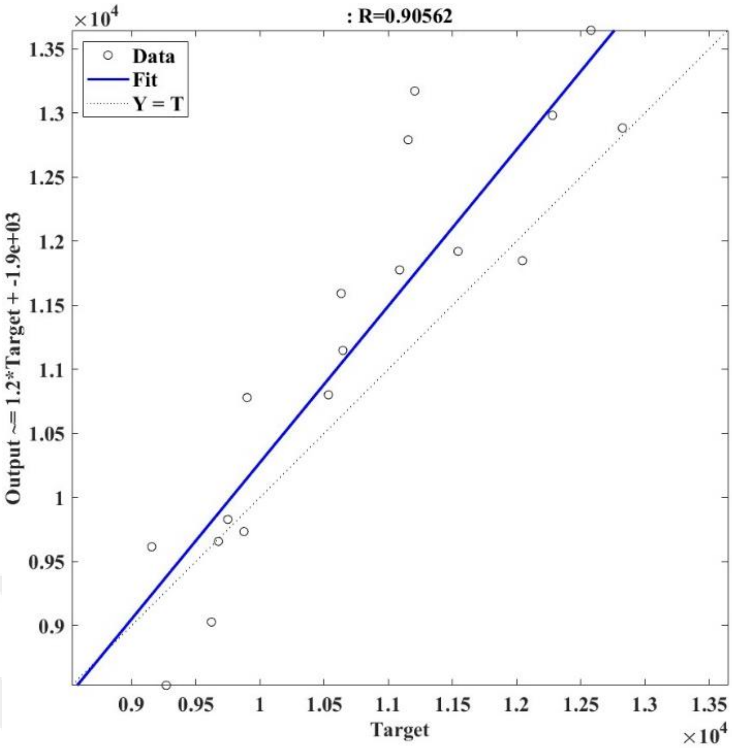


(b)

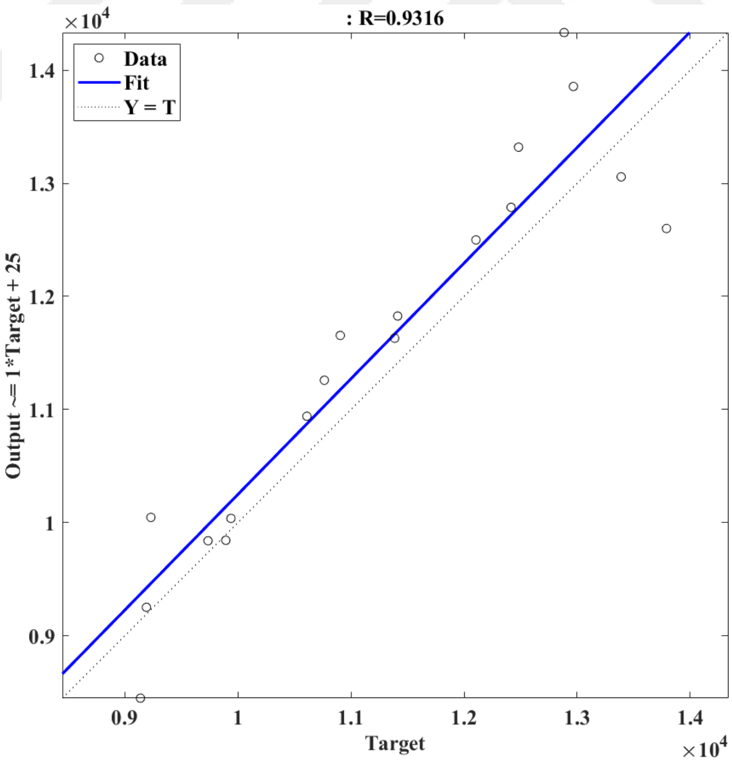


(c)

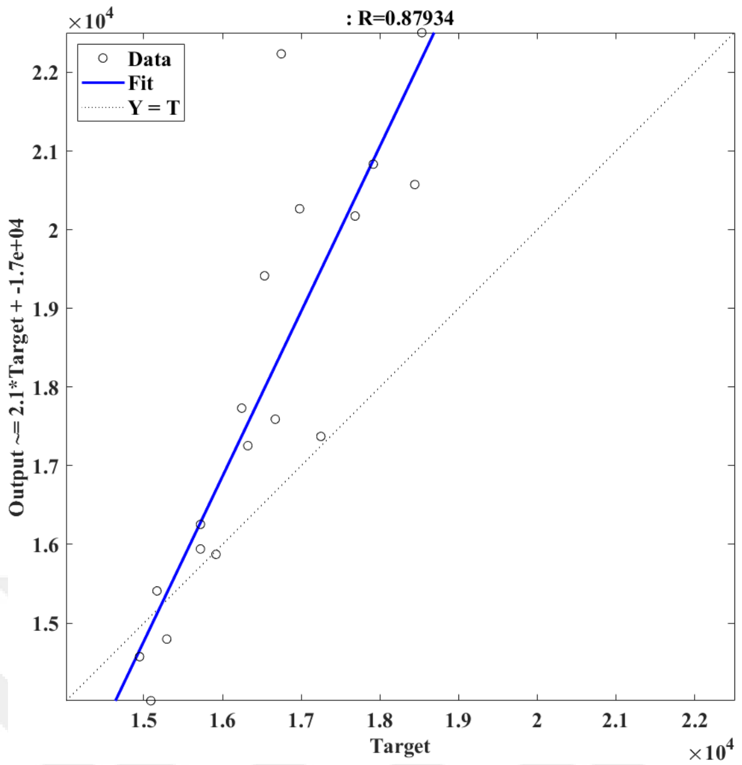
Figure 4.19. Prediction performance of the proposed LSTM model over test data for the total load in (a) Adana, (b) Mersin, and (c) Antalya provinces.


×10^4
: R=0.90562
Data
Fit
Y = T
Output ~= 1.2*Target + -1.9e+03
1.35
1.3
1.25
1.2
1.15
1.1
1.05
1
0.95
0.9
0.9 0.95 1 1.05 1.1 1.15 1.2 1.25 1.3 1.35
Target
×10^4

(a)

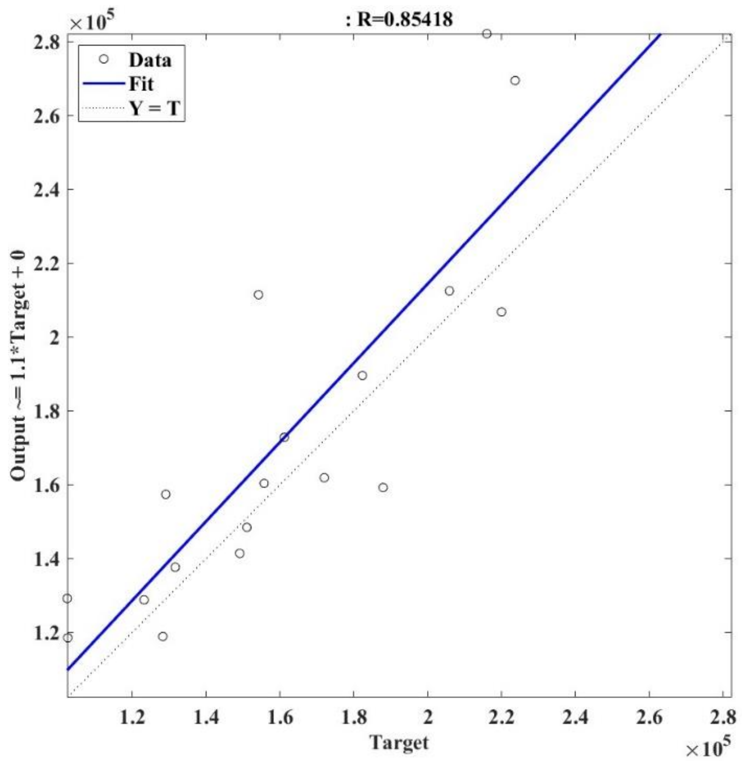

×10^4
: R=0.9316
Data
Fit
Y = T
Output ~= 1*Target + 25
1.4
1.3
1.2
1.1
1
0.9
0.9 1 1.1 1.2 1.3 1.4
Target
×10^4

(b)

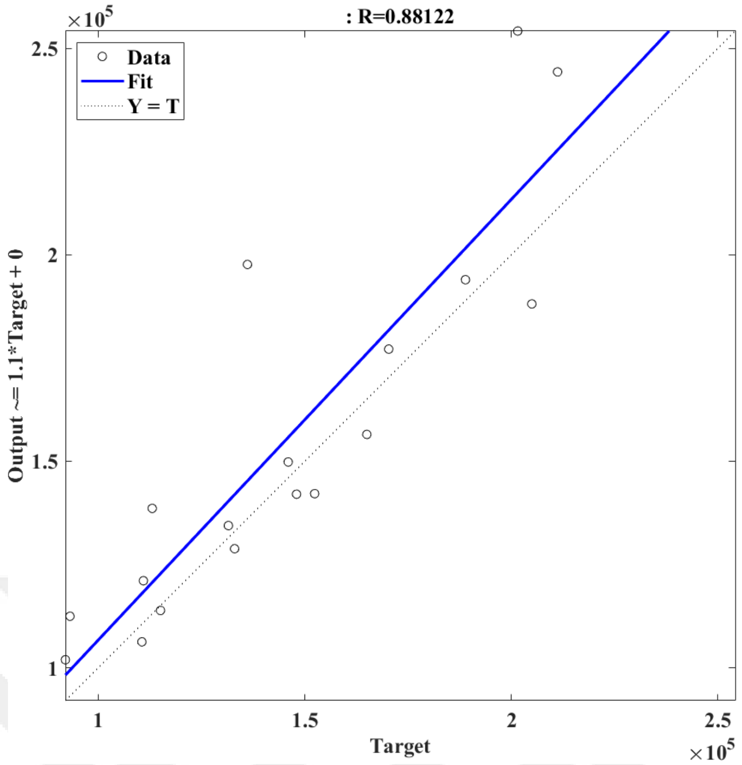


(c)

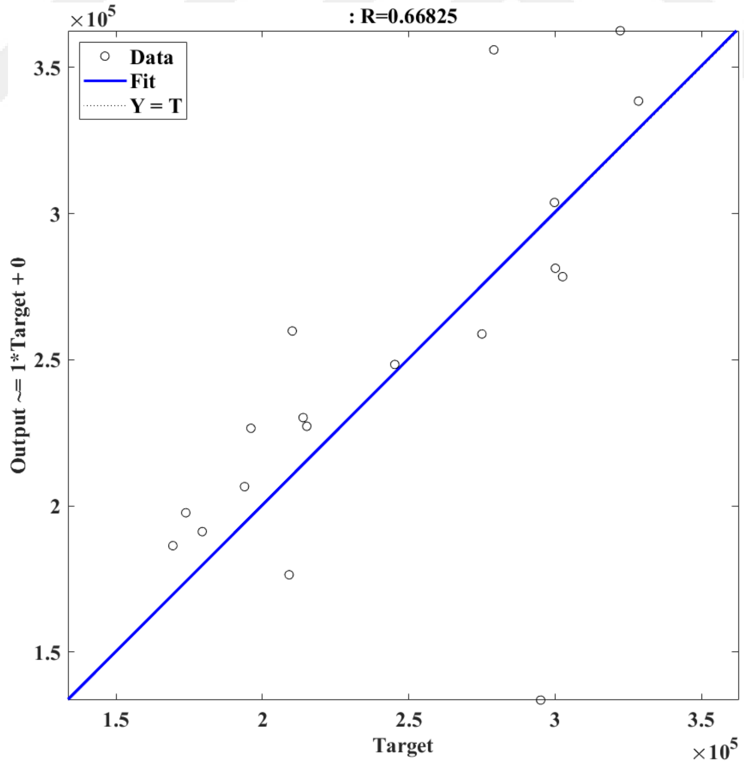
Figure 4.20. Linear regression graphs of the LSTM model for the lighting load in (a) Adana, (b) Mersin, and (c) Antalya province.



(a)

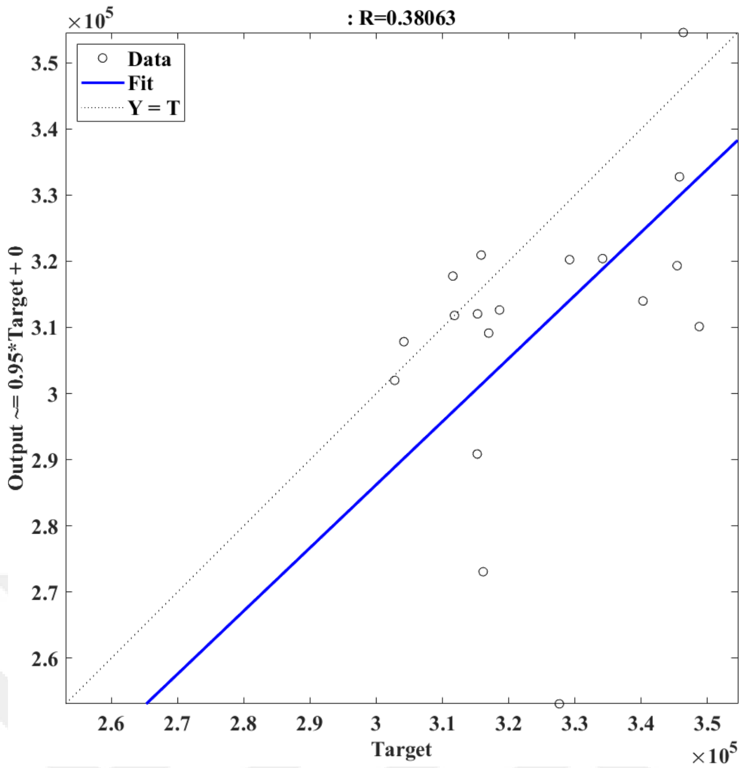


(b)

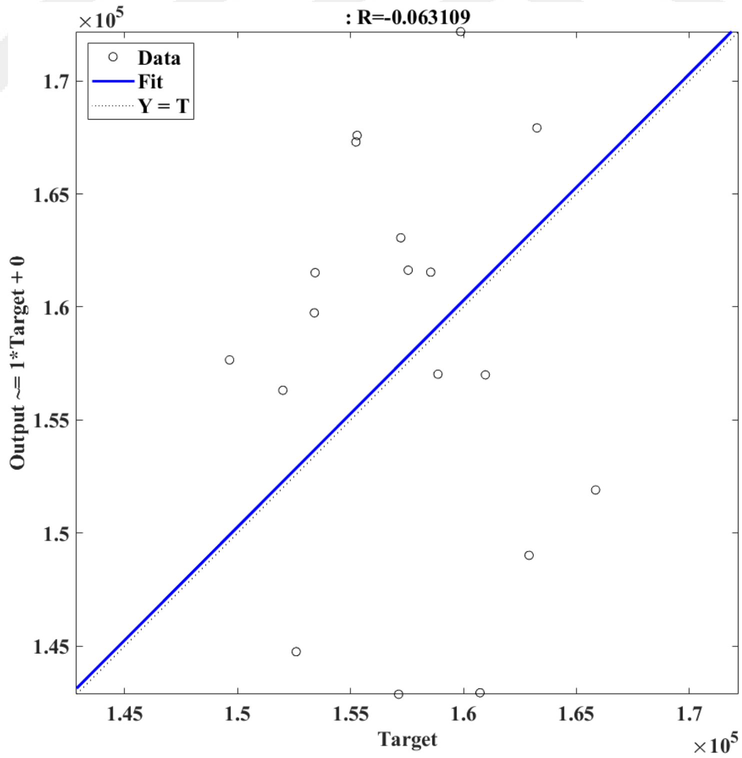


(c)

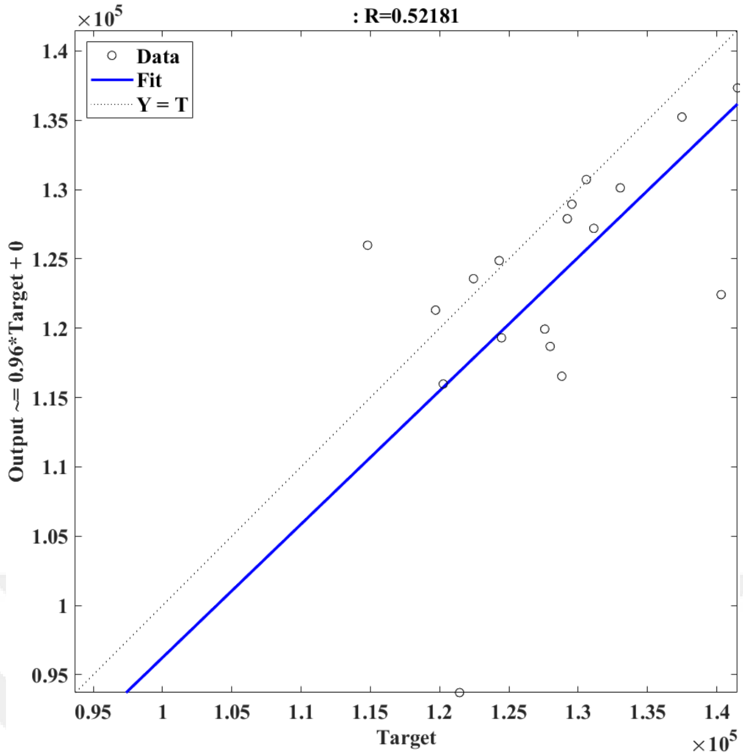
Figure 4.21. Linear regression graphs of the proposed LSTM model for the residential load in (a) Adana, (b) Mersin, and (c) Antalya provinces.


: R=0.38063
Data
Fit
Y = T
Output ~= 0.95*Target + 0
Target
$\times 10^5$

(a)

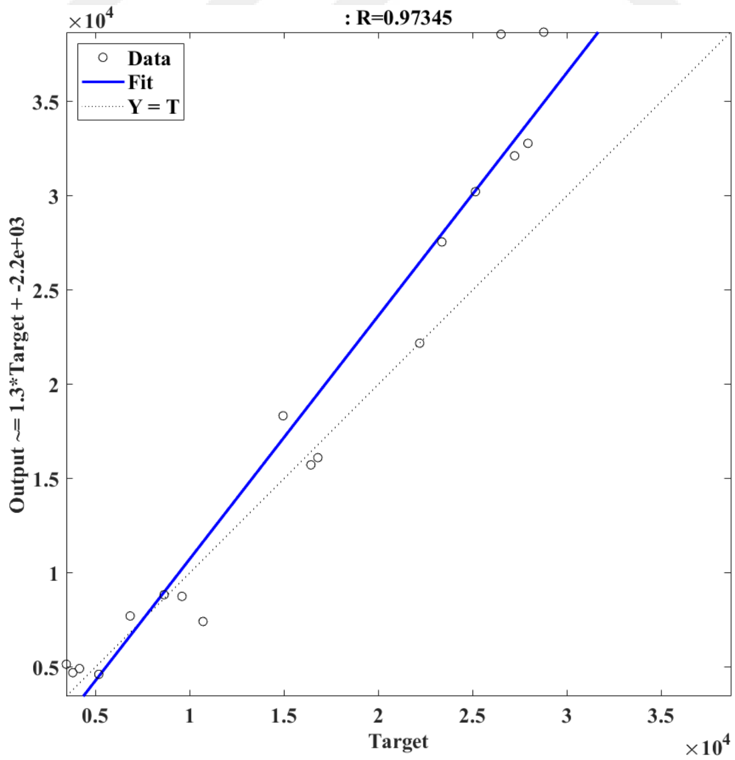

: R=-0.063109
Data
Fit
Y = T
Output ~= 1*Target + 0
Target
$\times 10^5$

(b)

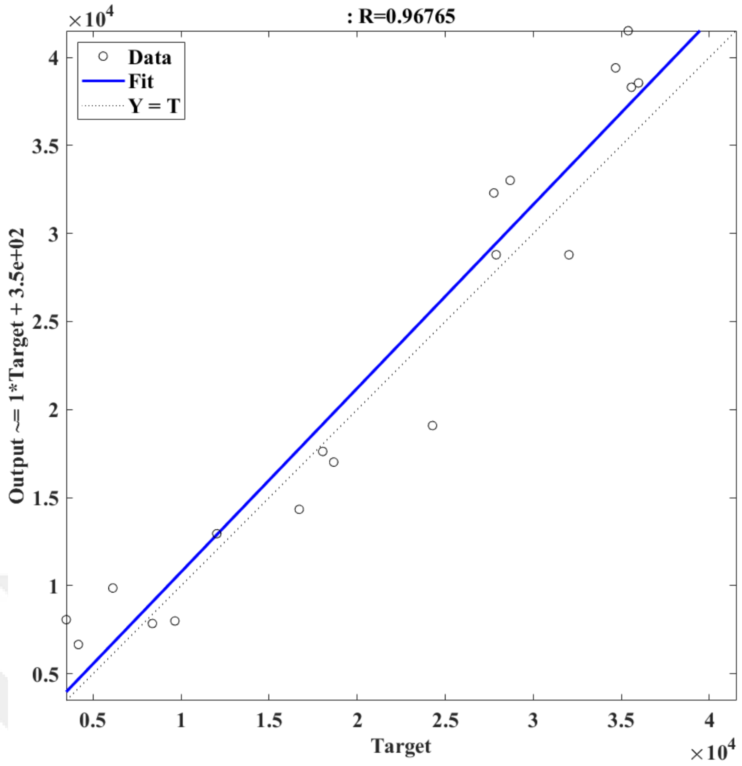


(c)

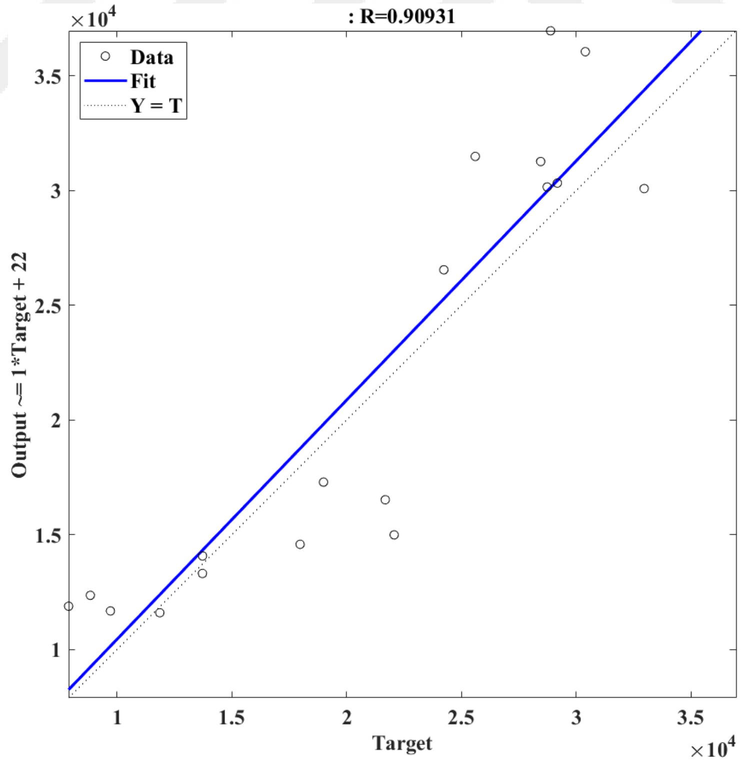
Figure 4.22. Linear regression graphs of the proposed LSTM model for the industry load in (a) Adana, (b) Mersin, and (c) Antalya provinces.



(a)

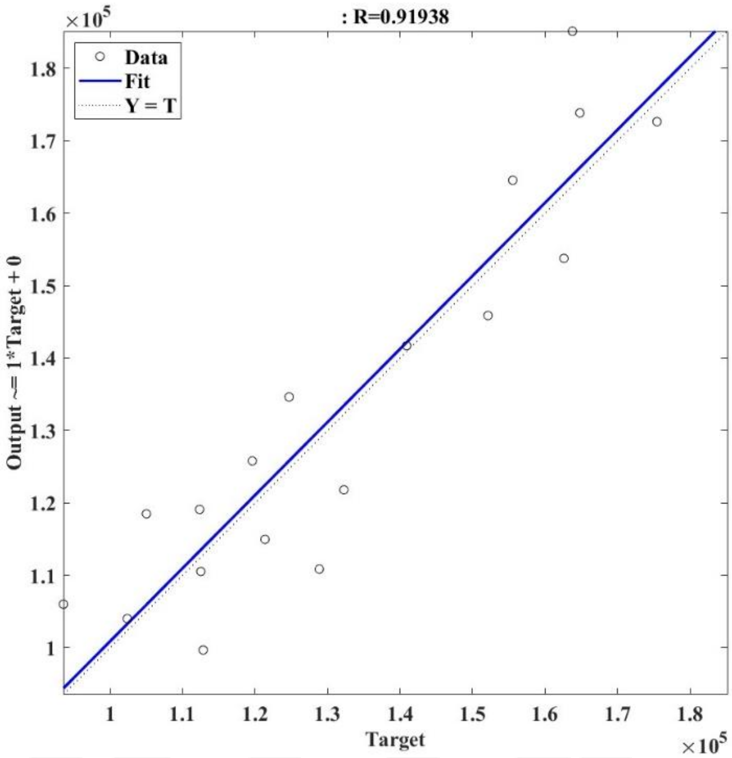


(b)

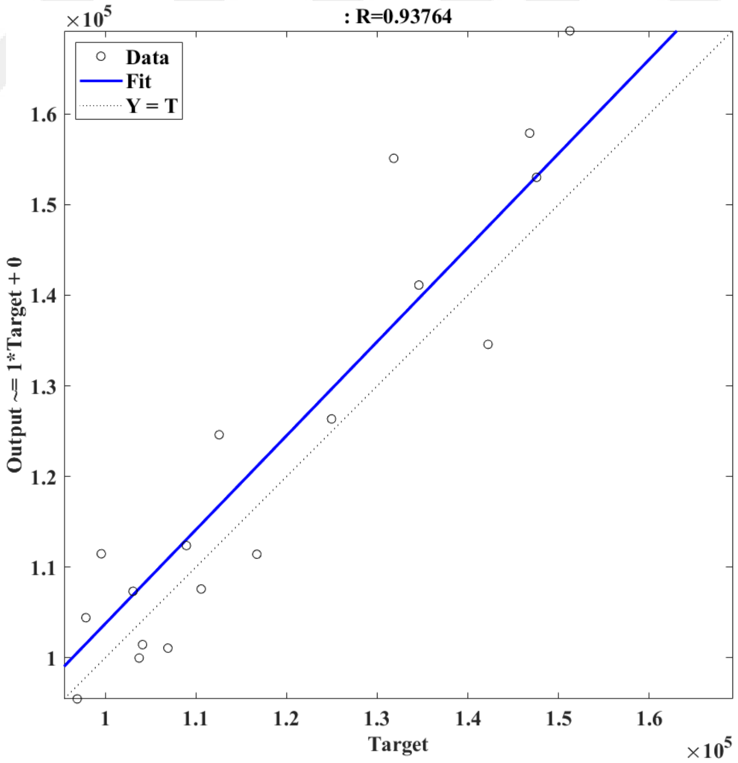


(c)

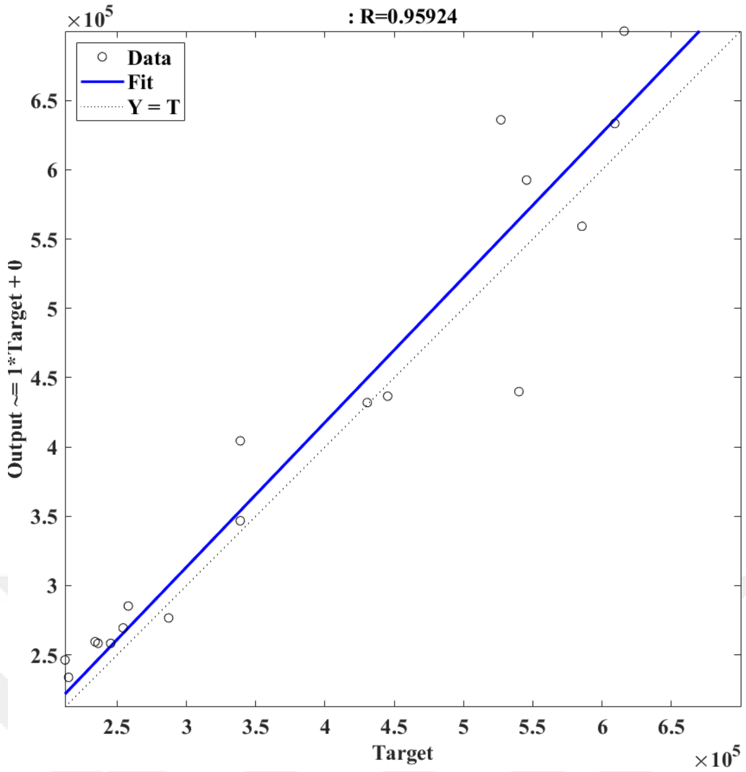
Figure 4.23. Linear regression graphs of the proposed LSTM model for the agriculture load in (a) Adana, (b) Mersin, and (c) Antalya provinces.


×10^5
: R=0.91938
Data
Fit
Y = T
Output ~= 1*Target + 0
Target
×10^5

(a)

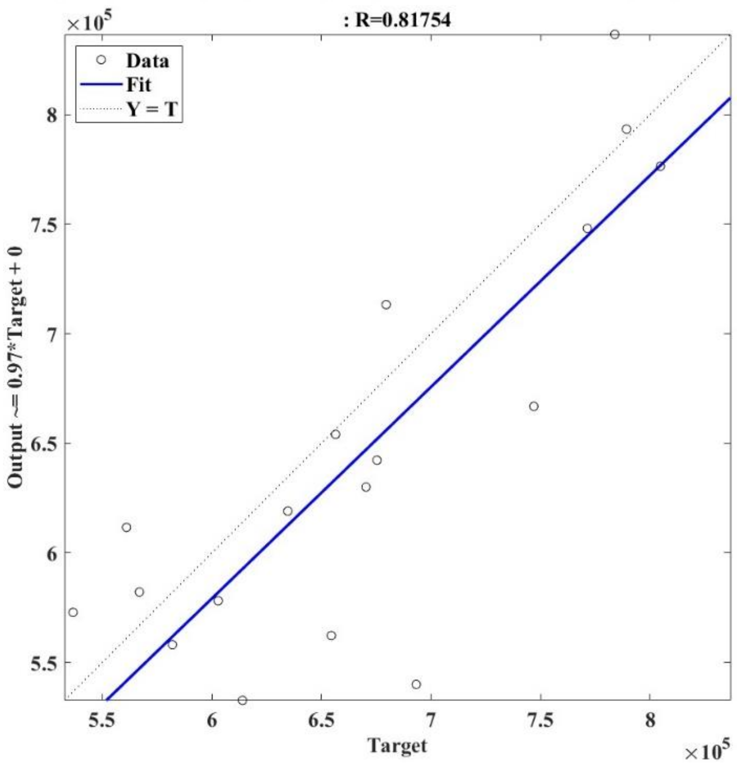

×10^5
: R=0.93764
Data
Fit
Y = T
Output ~= 1*Target + 0
Target
×10^5

(b)

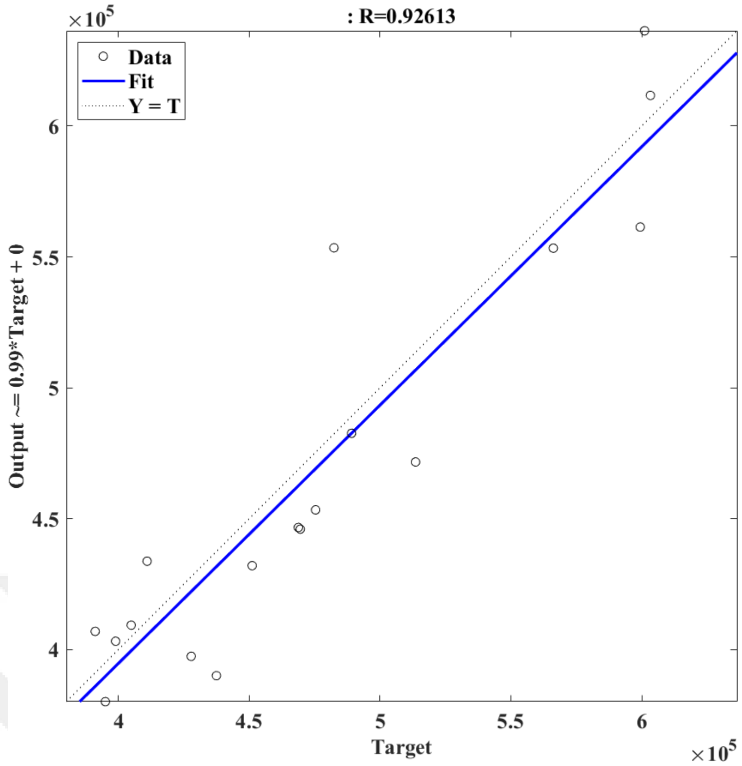


(c)

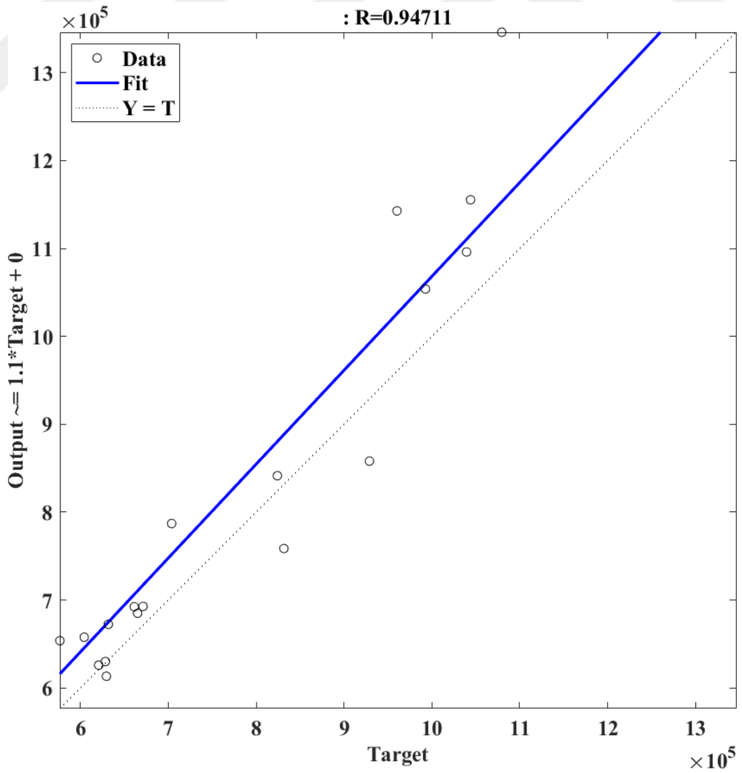
Figure 4.24. Linear regression graphs of the LSTM model for the commercial load in (a) Adana, (b) Mersin, and (c) Antalya provinces.



(a)



(b)



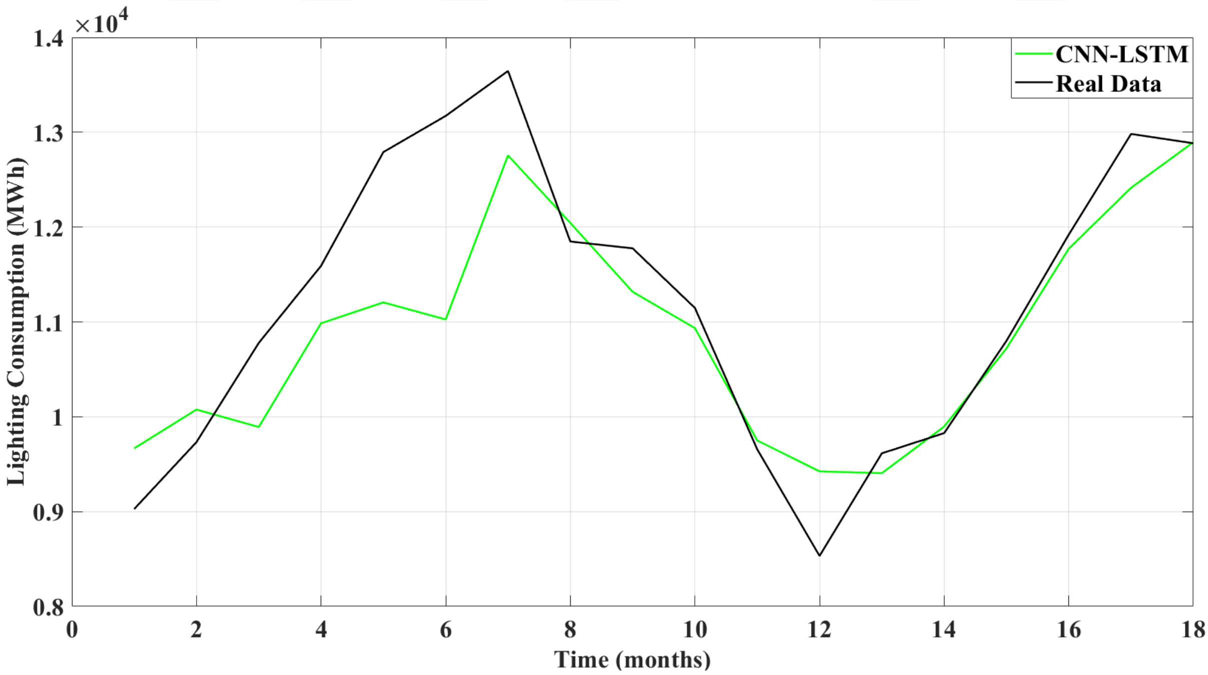
(c)

Figure 4.25. Linear regression graphs of the LSTM model for the total load in (a) Adana, (b) Mersin, and (c) Antalya provinces.

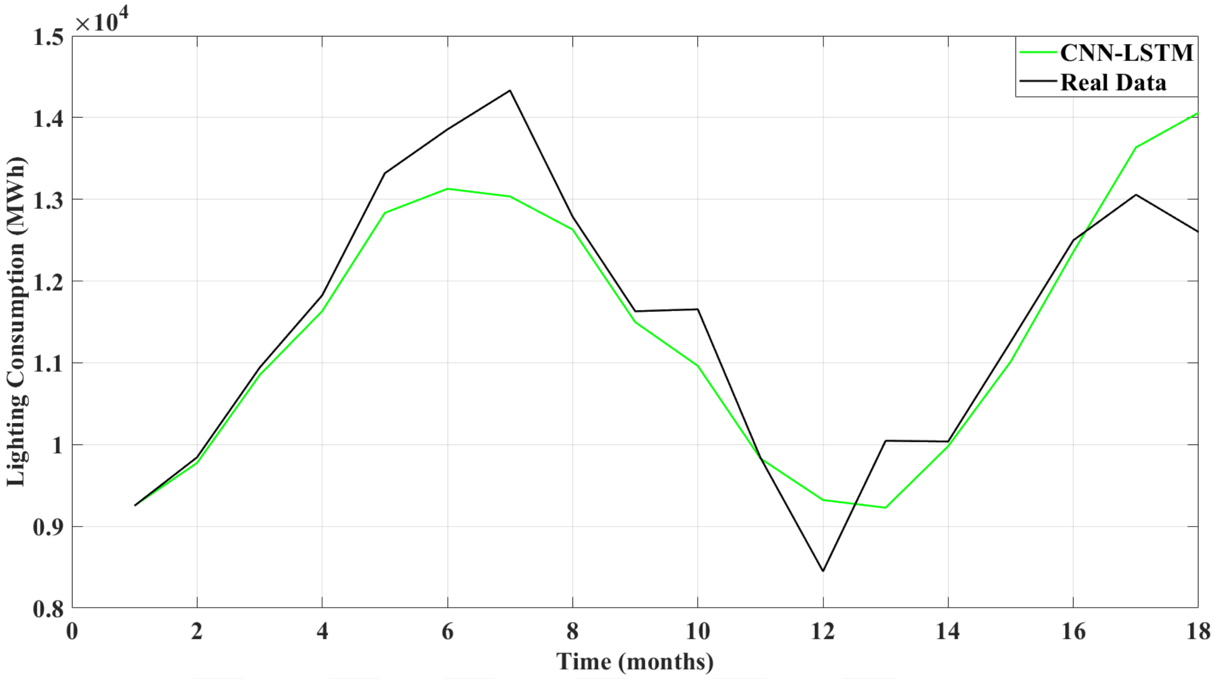
The LSTM model shows superior performance in forecasting sectoral electricity loads compared to the CNN method. This results in improved forecasting accuracy, as demonstrated by the lower error metrics and closer alignment between predicted and actual values in the LSTM results. Its ability to accurately predict load across various sectors highlights its potential for application in real-world energy management and planning. The next section presents a hybrid model to further enhance forecasting accuracy.

4.4. The Results of hybrid CNN-LSTM-Based Electricity Load Forecasting

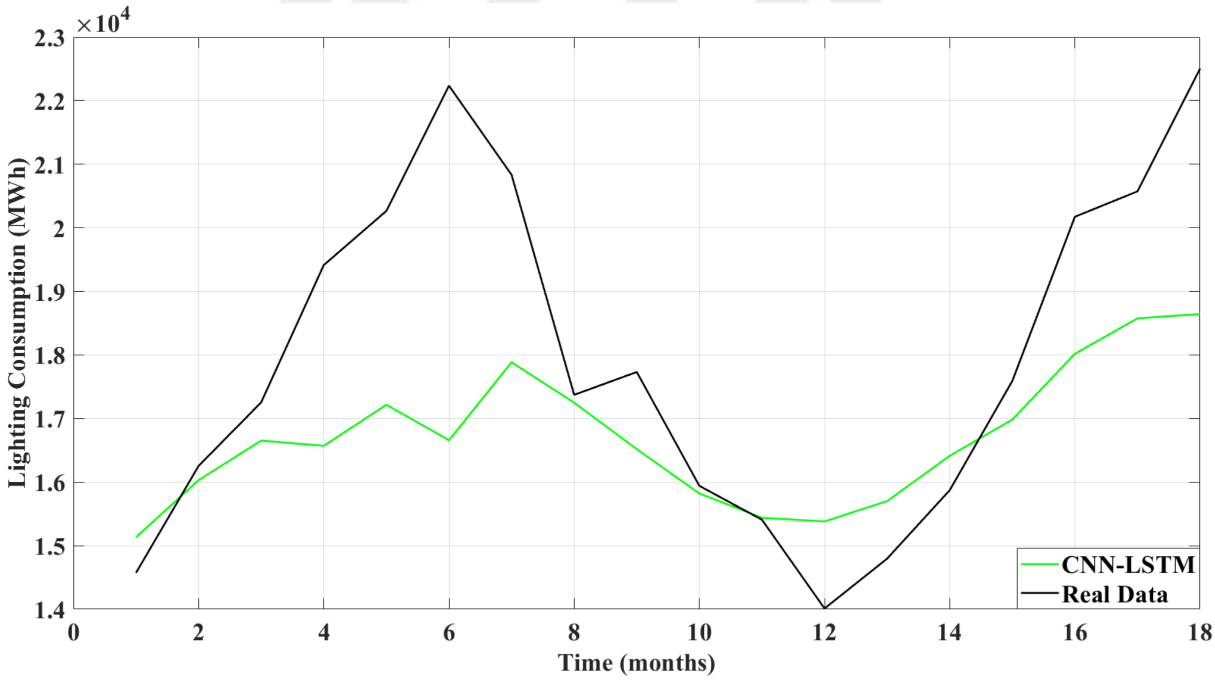
The CNN-LSTM model combines the feature extraction capabilities of CNN with the sequence learning abilities of LSTM to forecast sectoral electricity load in Adana, Mersin, and Antalya provinces. The Results of the CNN-LSTM hybrid model present for different sectors, demonstrate the model's accuracy and reliability. The prediction performance of the proposed CNN-LSTM model over test data for the sectoral electricity load is presented in Figures 4.26-4.31. Figures 4.32-4.37 show the CNN-LSTM hybrid model's forecast results for the sectoral electricity in Adana, Mersin, and Antalya provinces.



(a)

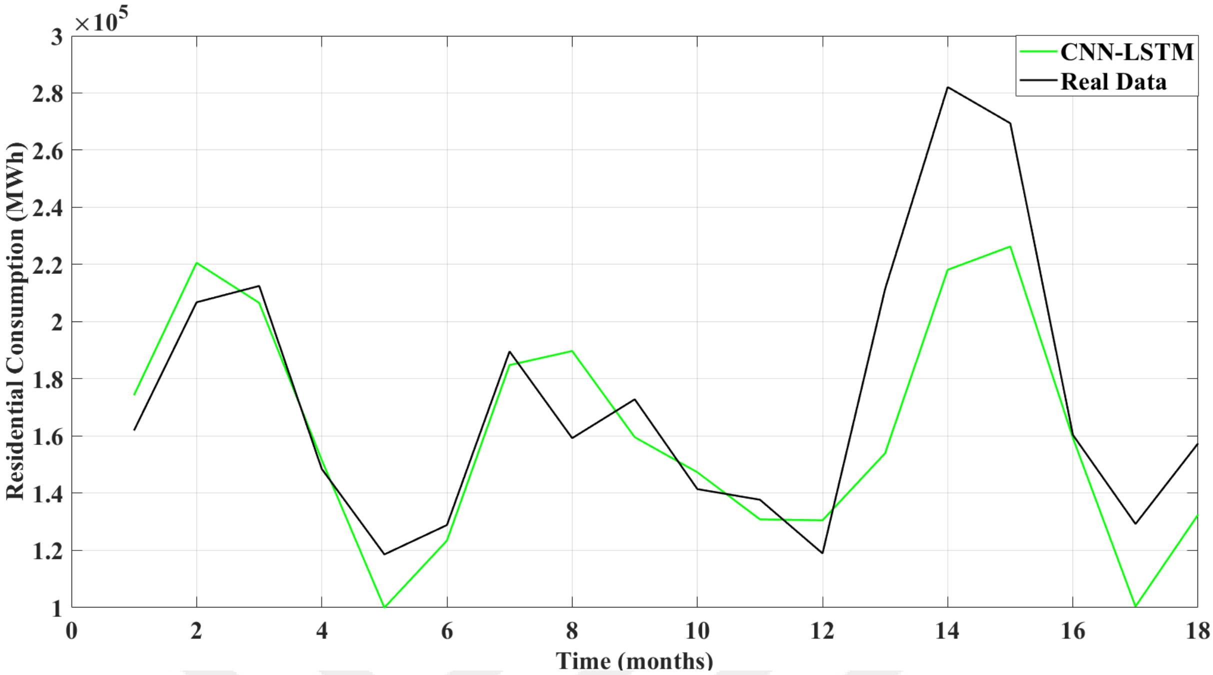


(b)



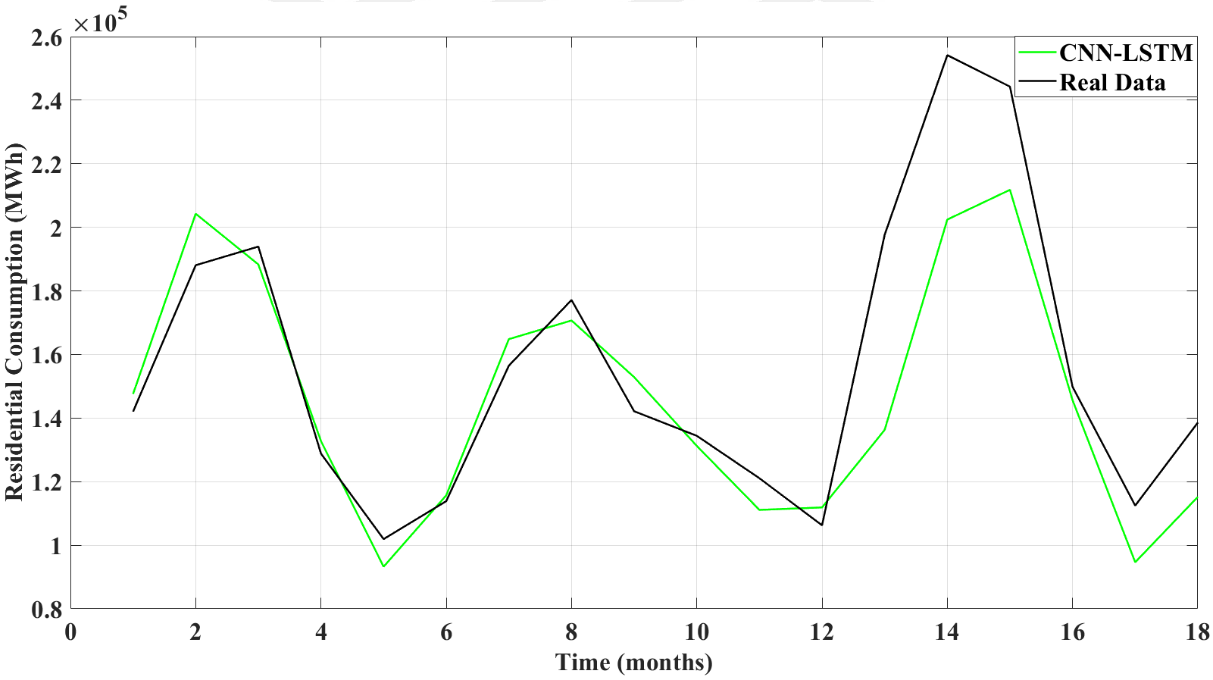
(c)

Figure 4.26. Prediction performance of the proposed CNN-LSTM model over test data for the lighting load in (a) Adana, (b) Mersin, and (c) Antalya provinces.



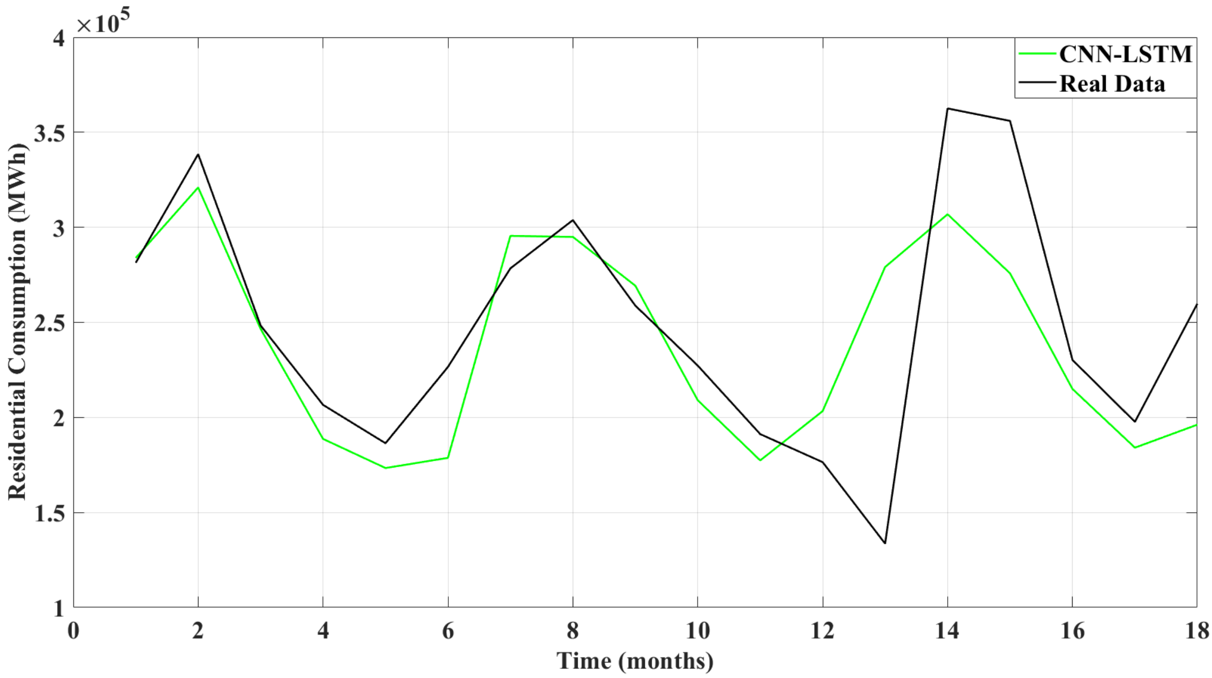
×10^5
CNN-LSTM
Real Data
Residential Consumption (MWh)
Time (months)

(a)



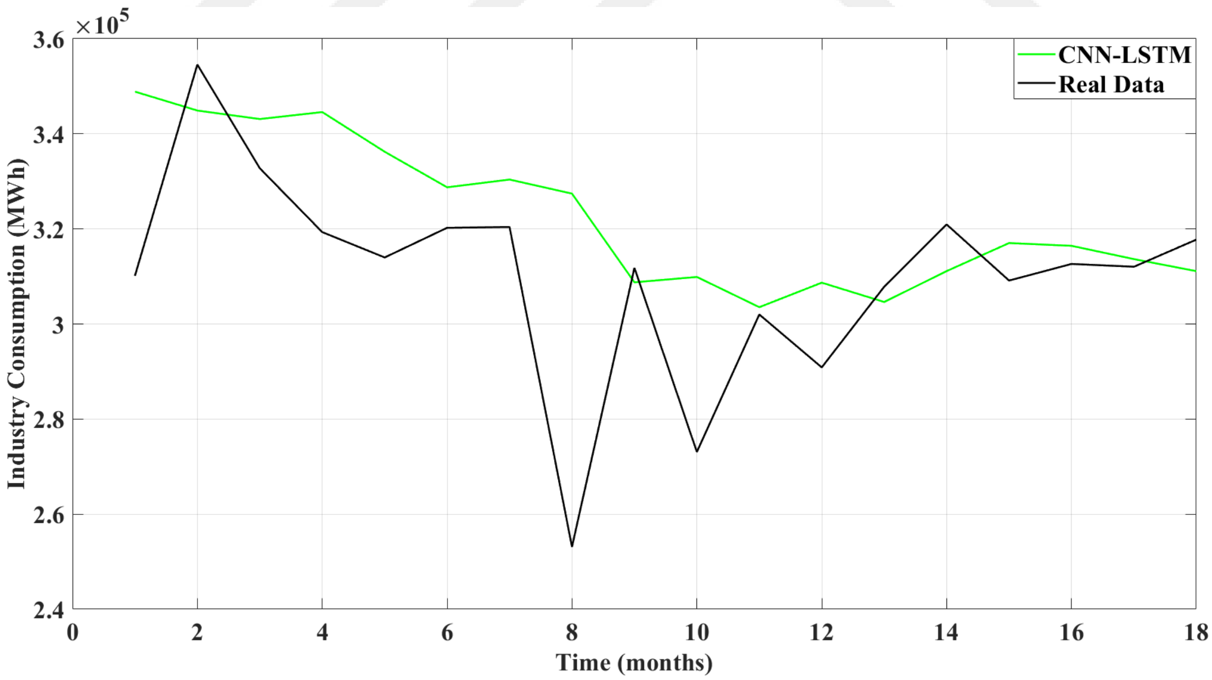
×10^5
CNN-LSTM
Real Data
Residential Consumption (MWh)
Time (months)

(b)

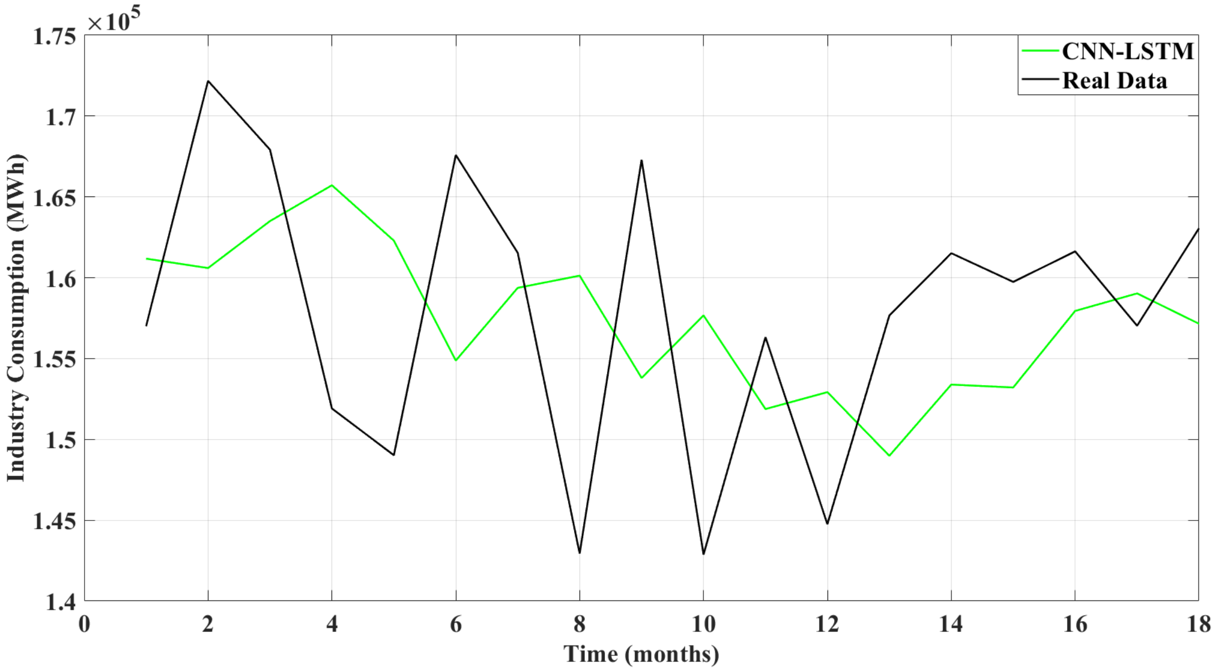


(c)

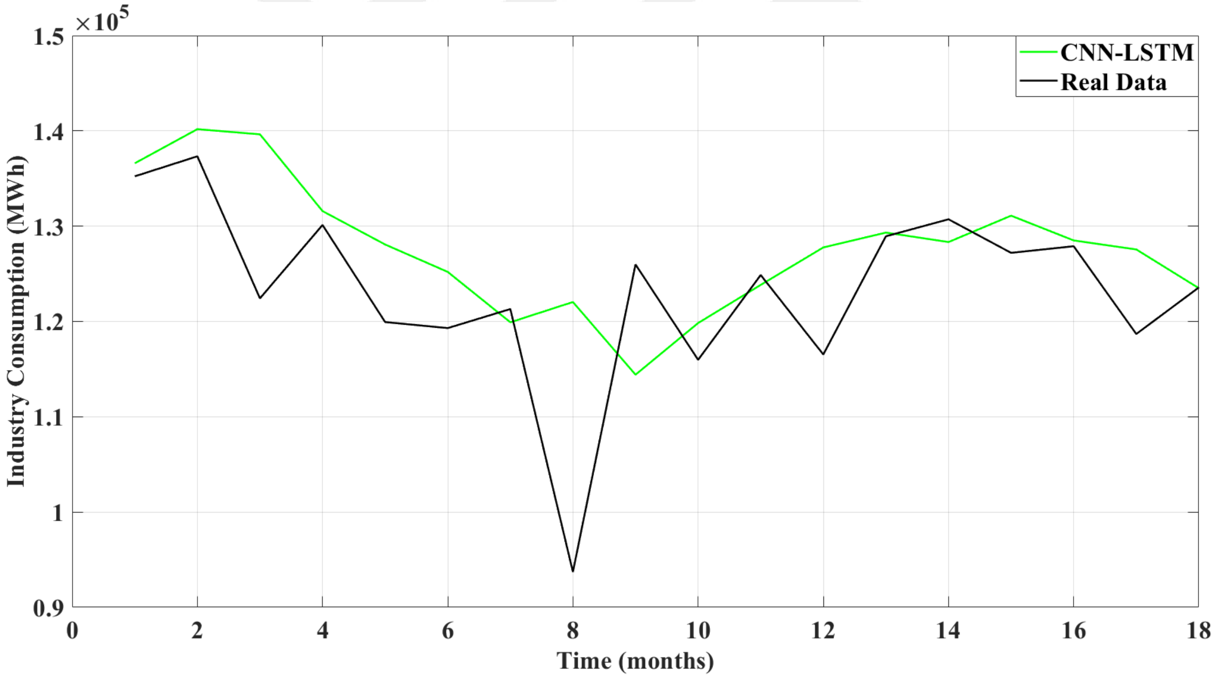
Figure 4.27. Prediction performance of the proposed CNN-LSTM model over test data for the residential load in (a) Adana, (b) Mersin, and (c) Antalya provinces.



(a)

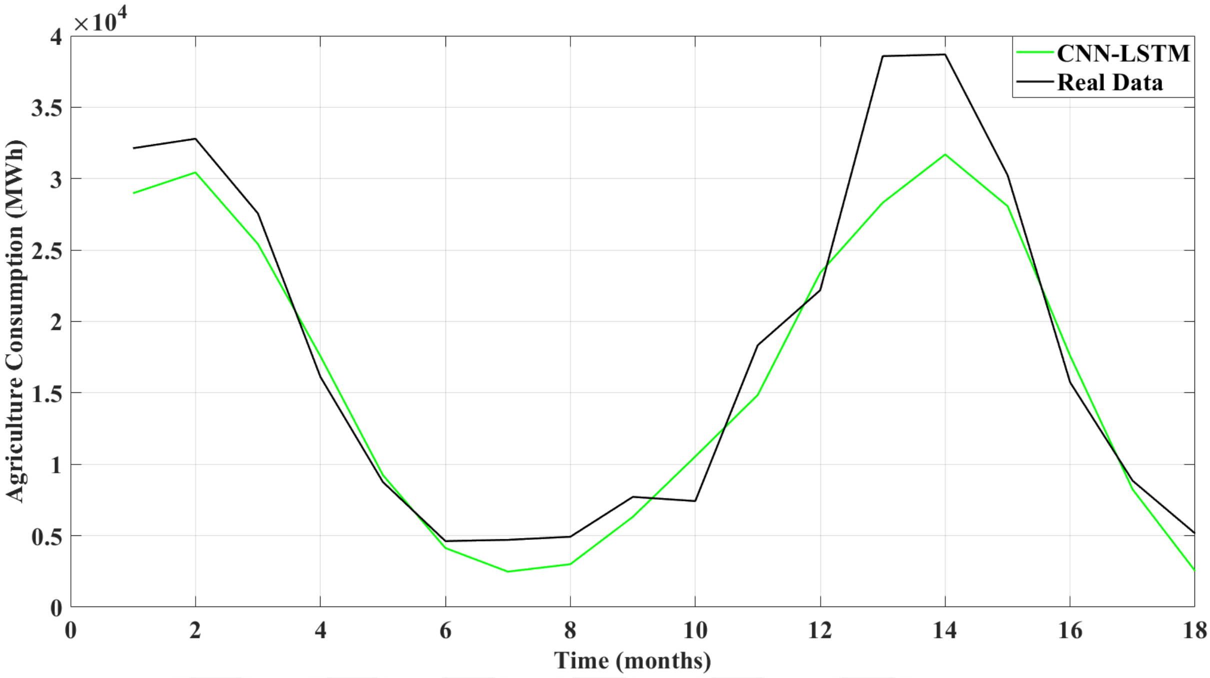


(b)

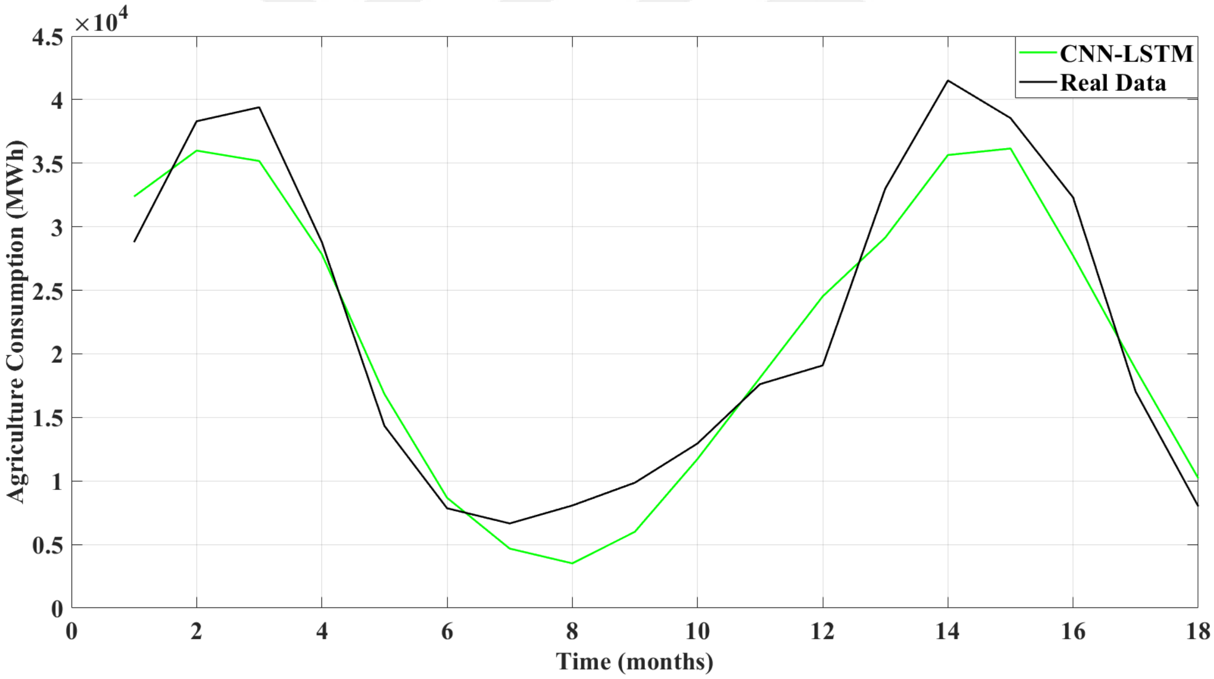


(c)

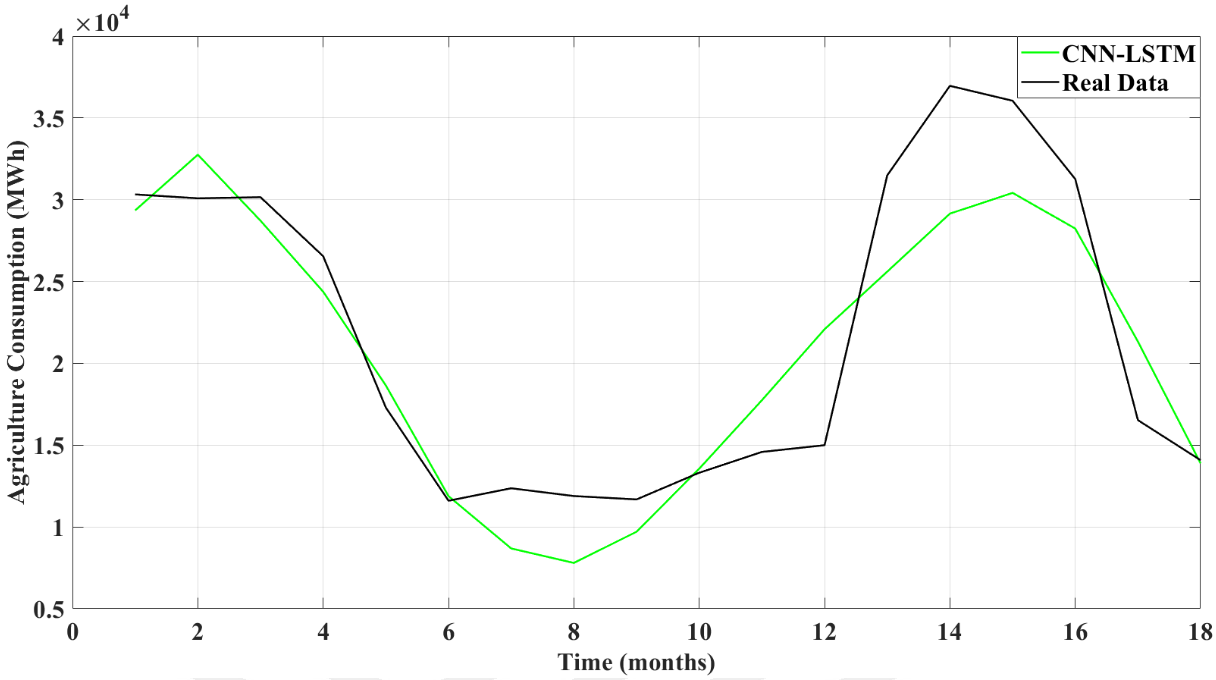
Figure 4.28. Prediction performance of the proposed CNN-LSTM model over test data for the industry load in (a) Adana, (b) Mersin, and (c) Antalya provinces.


×10^4
Agriculture Consumption (MWh)
Time (months)
CNN-LSTM
Real Data
0
0.5
1
1.5
2
2.5
3
3.5
4
0
2
4
6
8
10
12
14
16
18

(a)

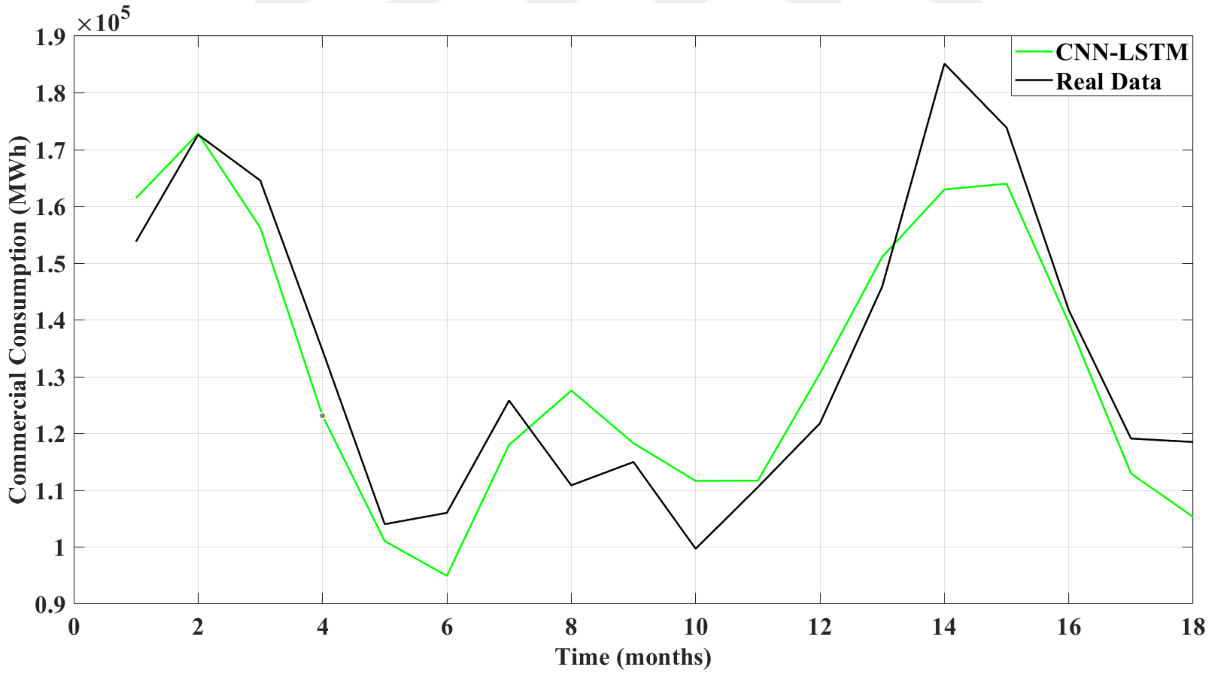

×10^4
Agriculture Consumption (MWh)
Time (months)
CNN-LSTM
Real Data
0
0.5
1
1.5
2
2.5
3
3.5
4
4.5
0
2
4
6
8
10
12
14
16
18

(b)

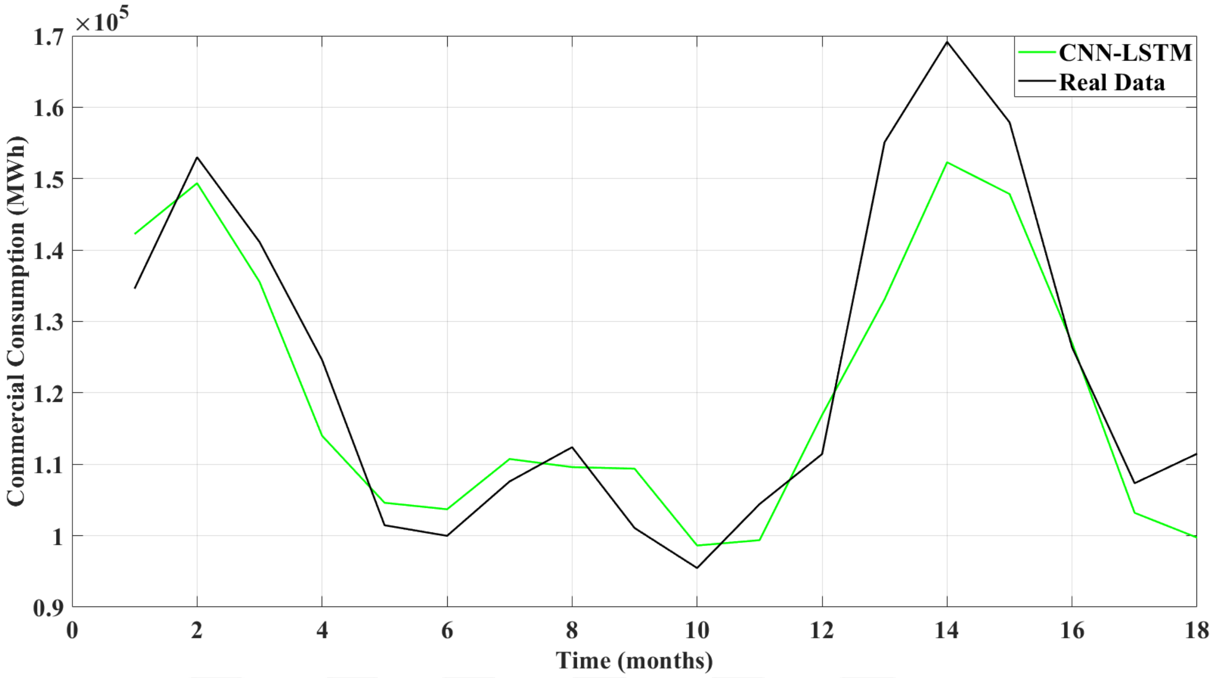


(c)

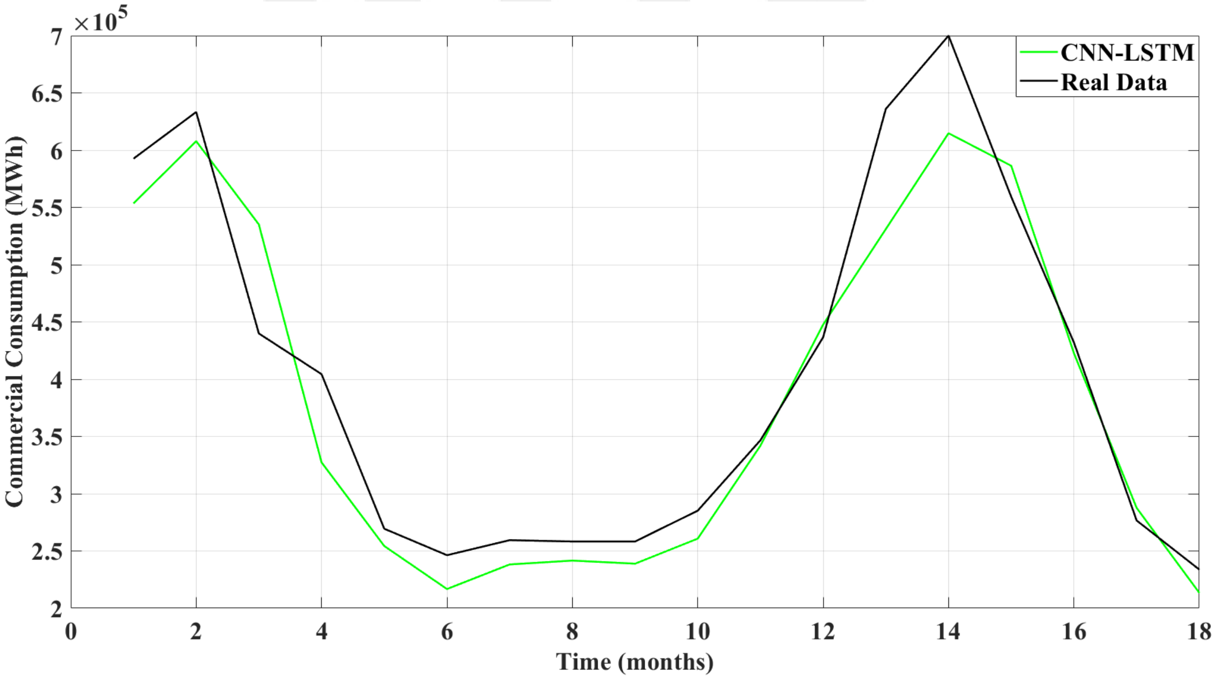
Figure 4.29. Prediction performance of the proposed CNN-LSTM model over test data for the agriculture load in (a) Adana, (b) Mersin, and (c) Antalya provinces.



(a)

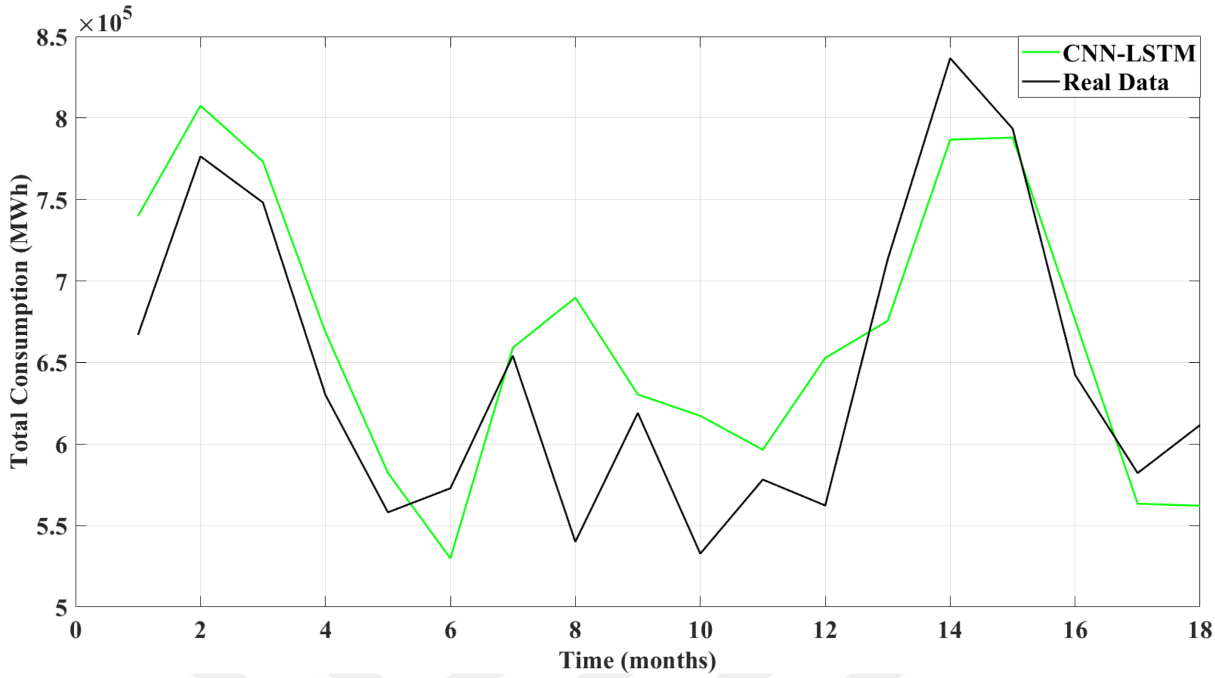


(b)



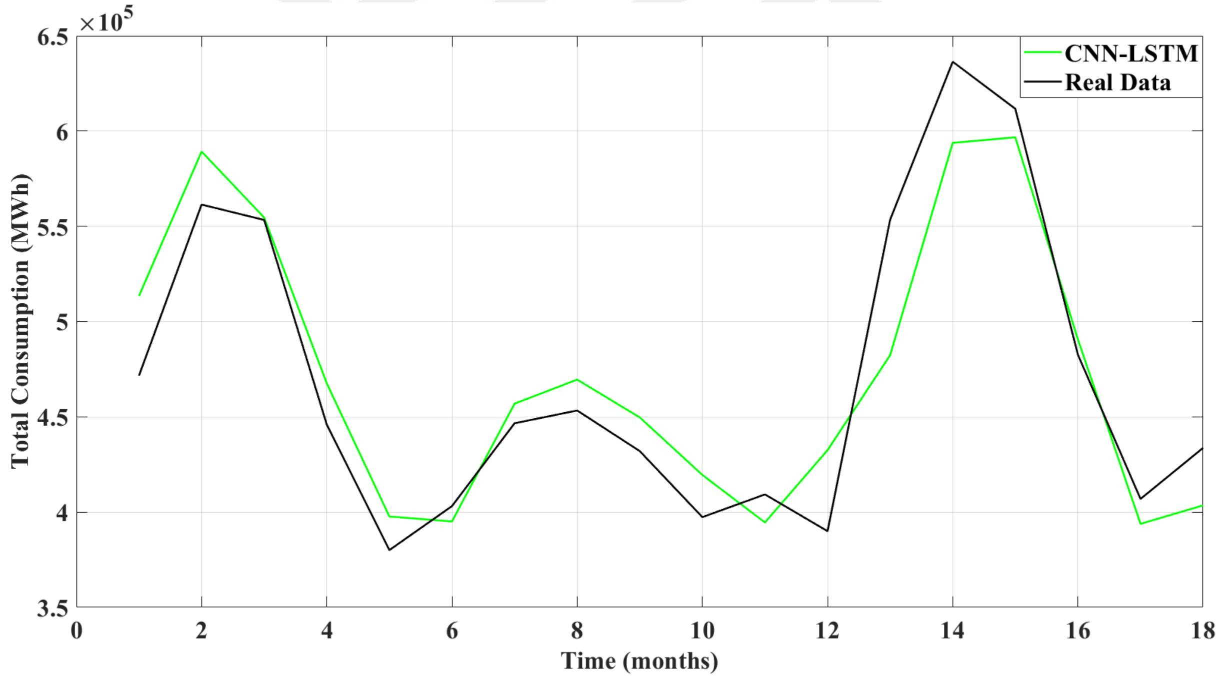
(c)

Figure 4.30. Prediction performance of the proposed CNN-LSTM model over test data for the commercial load in (a) Adana, (b) Mersin, and (c) Antalya provinces.



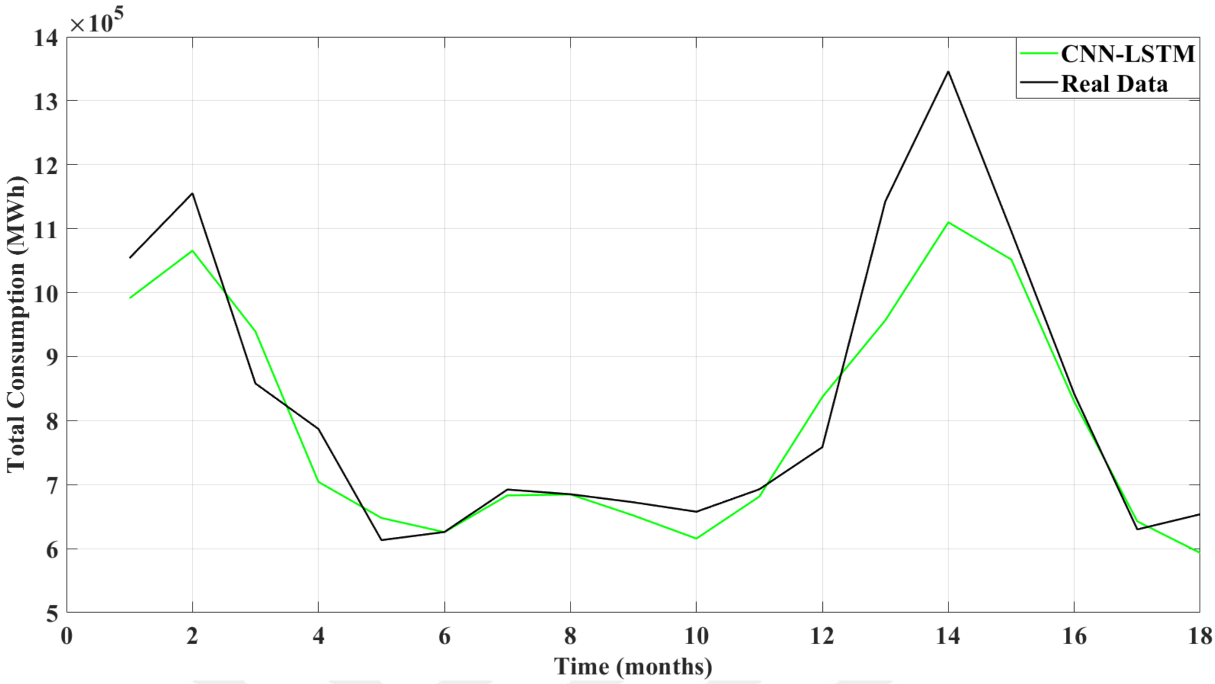
$\times 10^5$
8.5
8
7.5
7
6.5
6
5.5
5
Total Consumption (MWh)
0
2
4
6
8
10
12
14
16
18
Time (months)
CNN-LSTM
Real Data

(a)



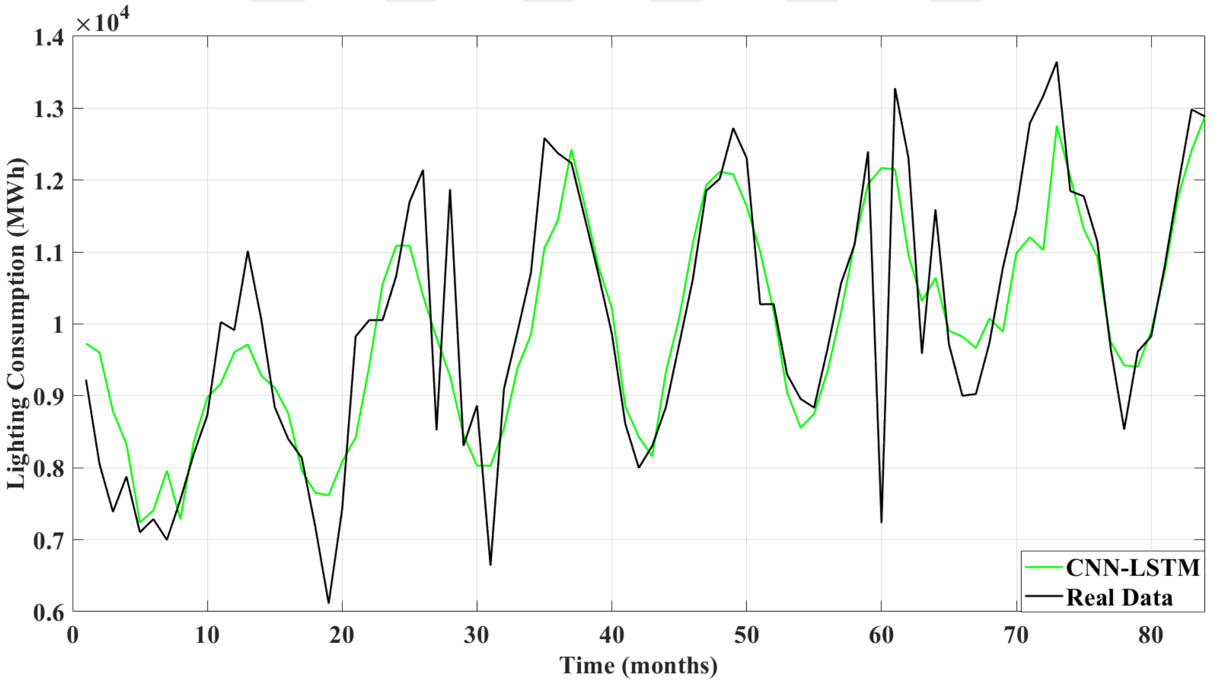
$\times 10^5$
6.5
6
5.5
5
4.5
4
3.5
Total Consumption (MWh)
0
2
4
6
8
10
12
14
16
18
Time (months)
CNN-LSTM
Real Data

(b)

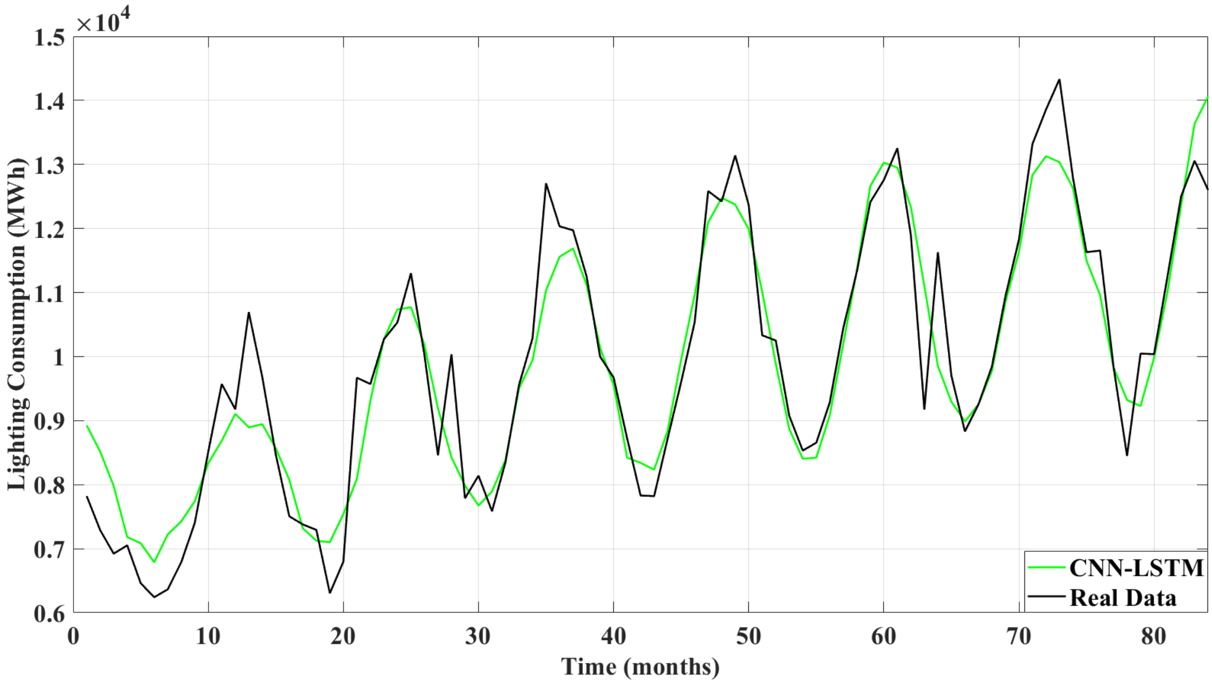


(c)

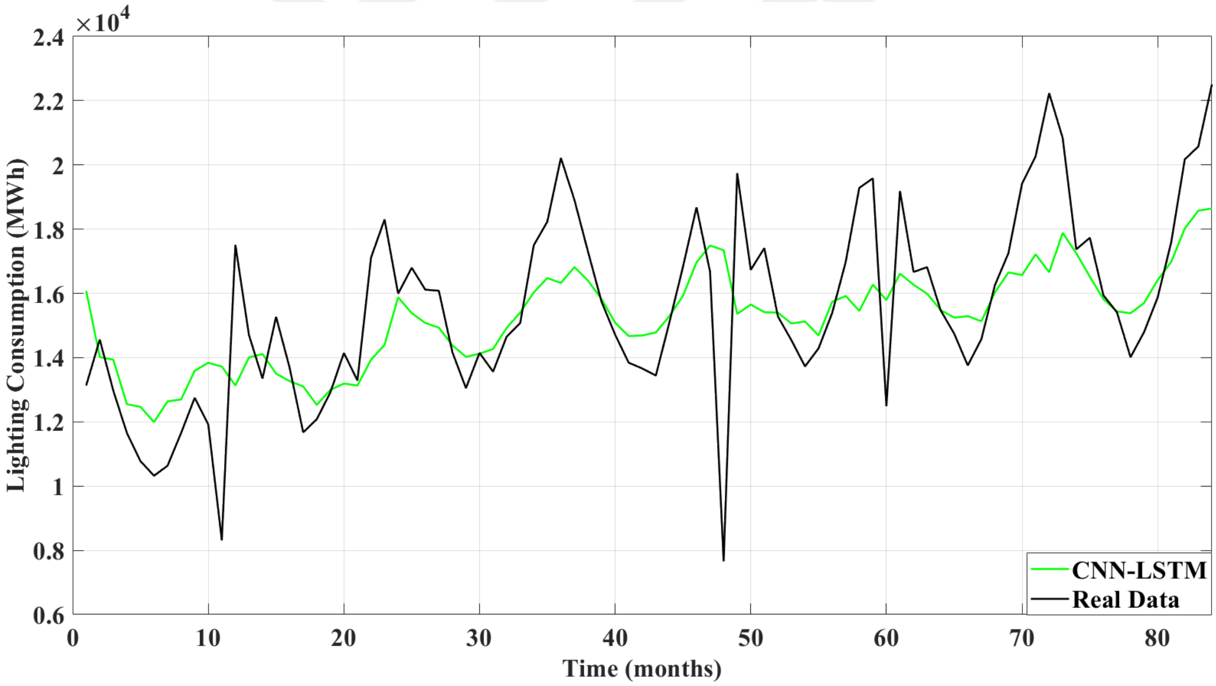
Figure 4.31. Prediction performance of the proposed CNN-LSTM model over test data for the total load in (a) Adana, (b) Mersin, and (c) Antalya provinces.



(a)

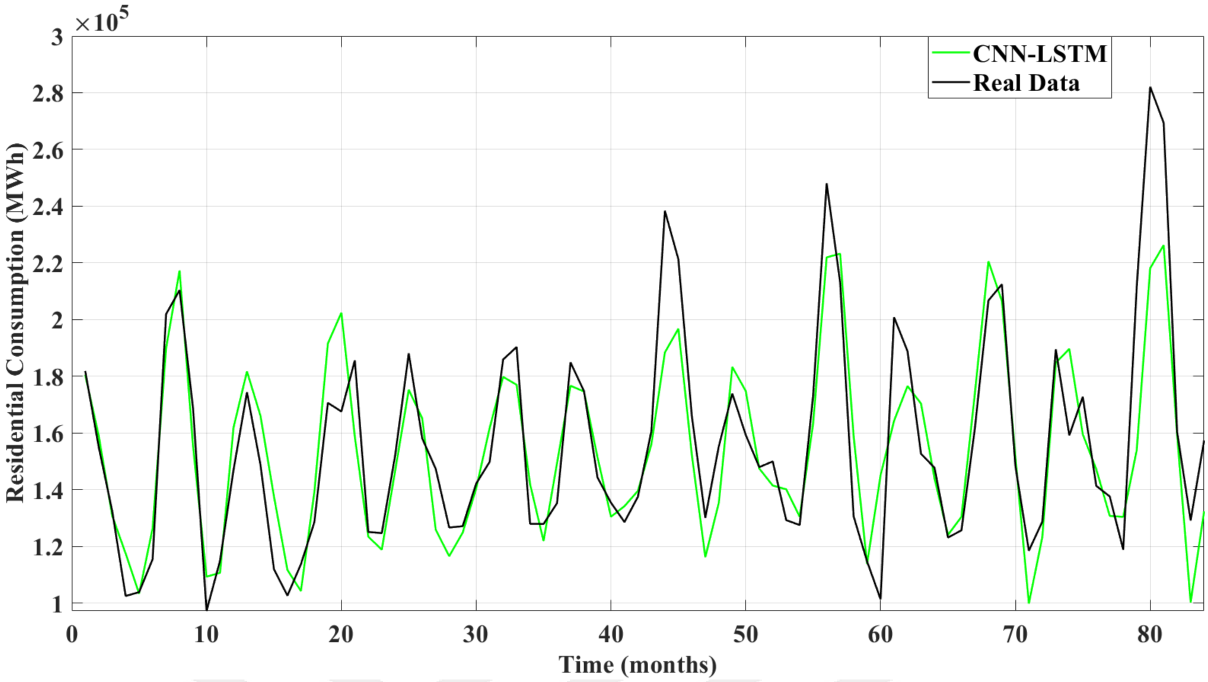


(b)

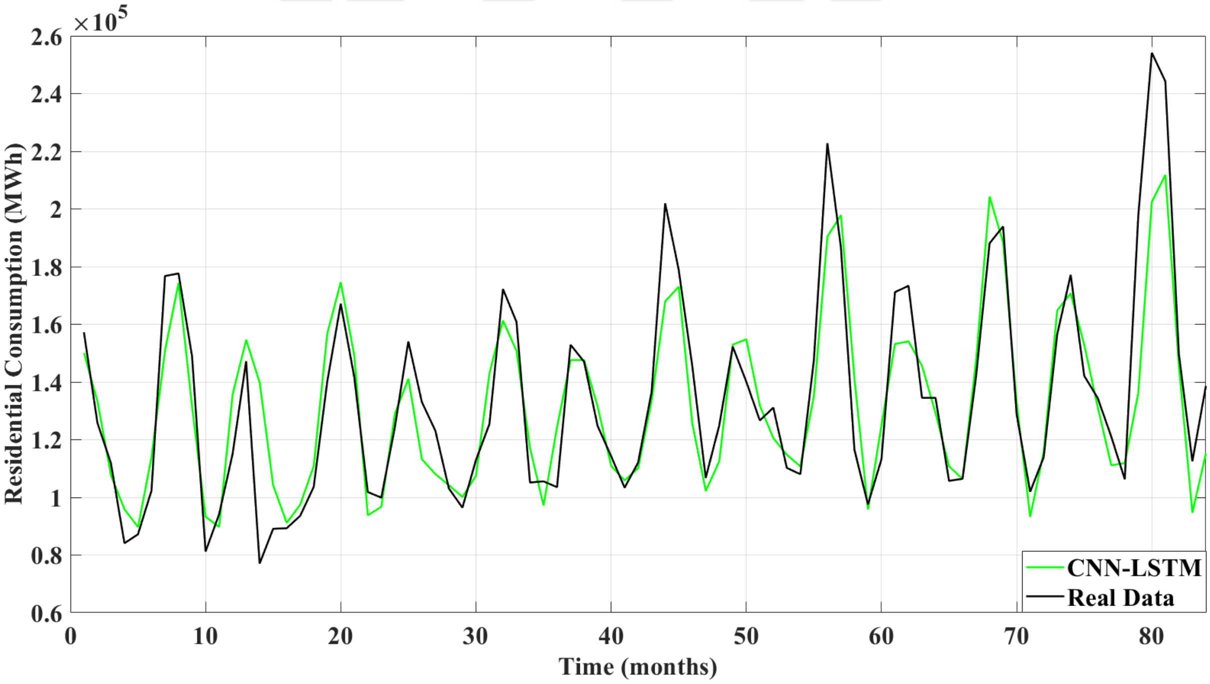


(c)

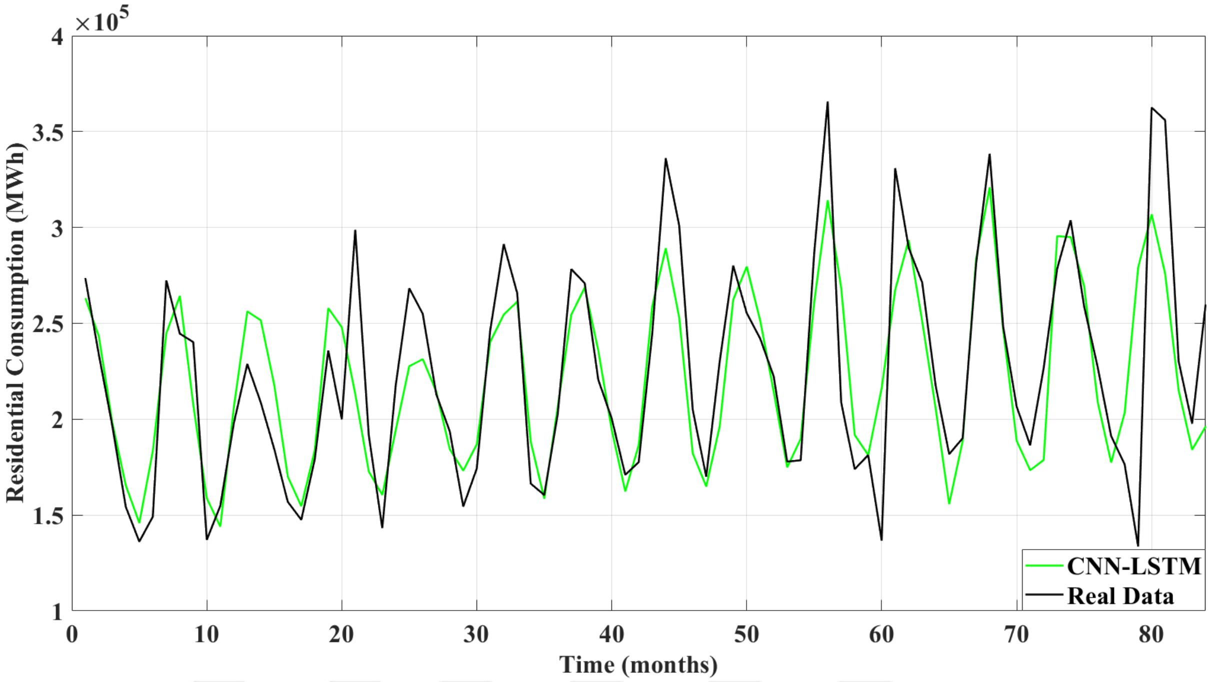
Figure 4.32. The CNN-LSTM model's forecast results for the lighting load in (a) Adana, (b) Mersin, and (c) Antalya provinces.


×10^5
Residential Consumption (MWh)
Time (months)
CNN-LSTM
Real Data

(a)

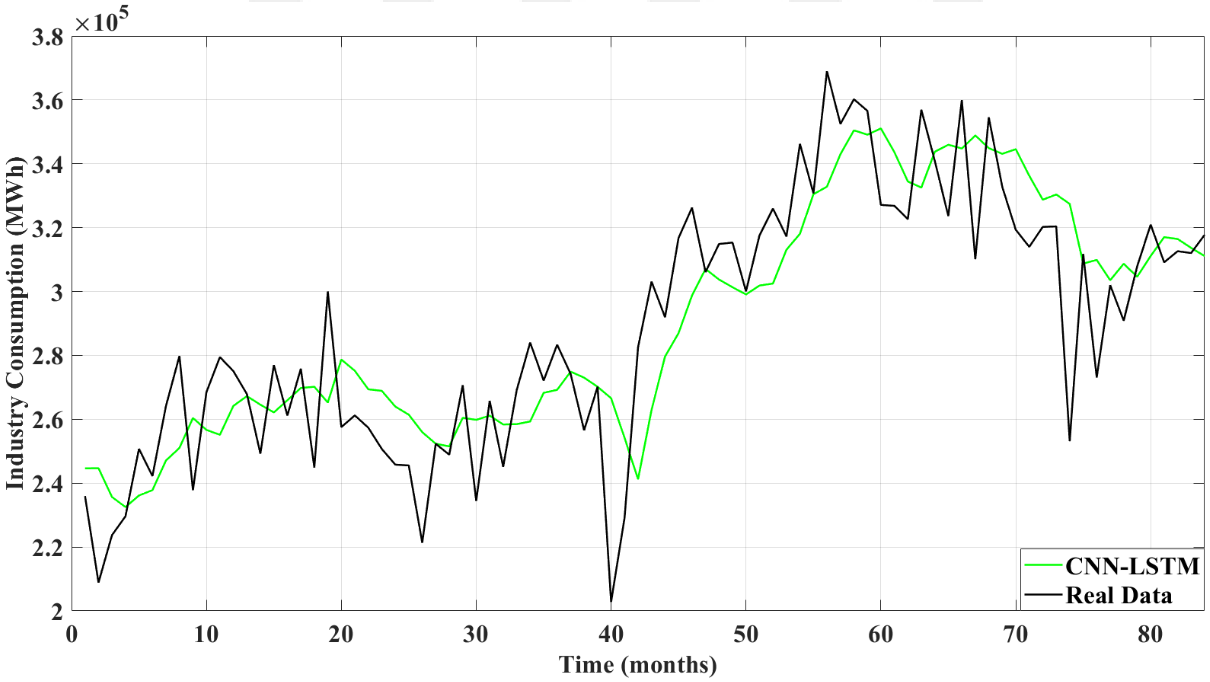

×10^5
Residential Consumption (MWh)
Time (months)
CNN-LSTM
Real Data

(b)

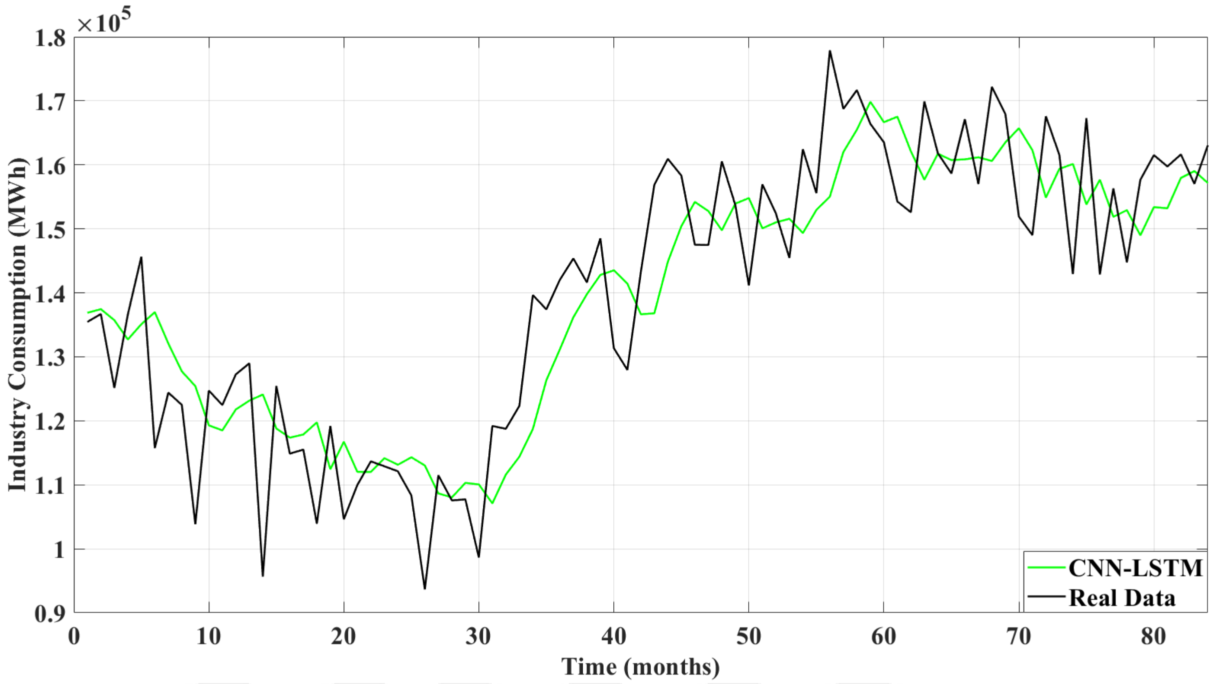


(c)

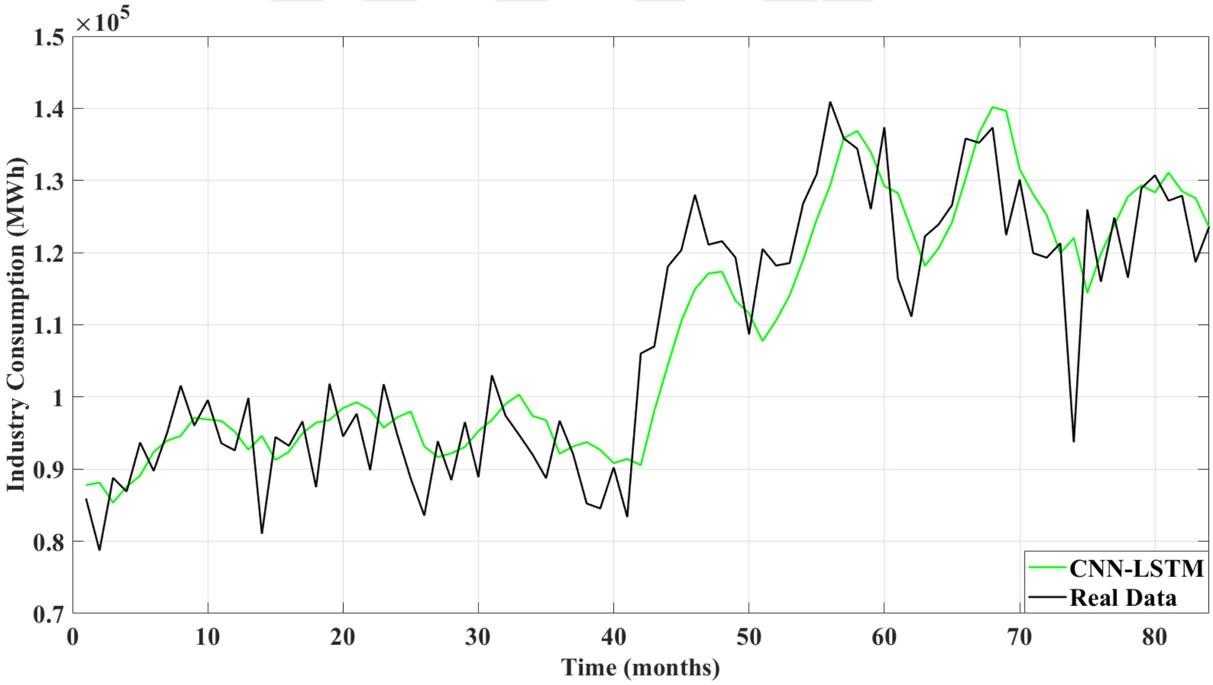
Figure 4.33. The CNN-LSTM model's forecast results for the residential load in (a) Adana, (b) Mersin, and (c) Antalya provinces.



(a)

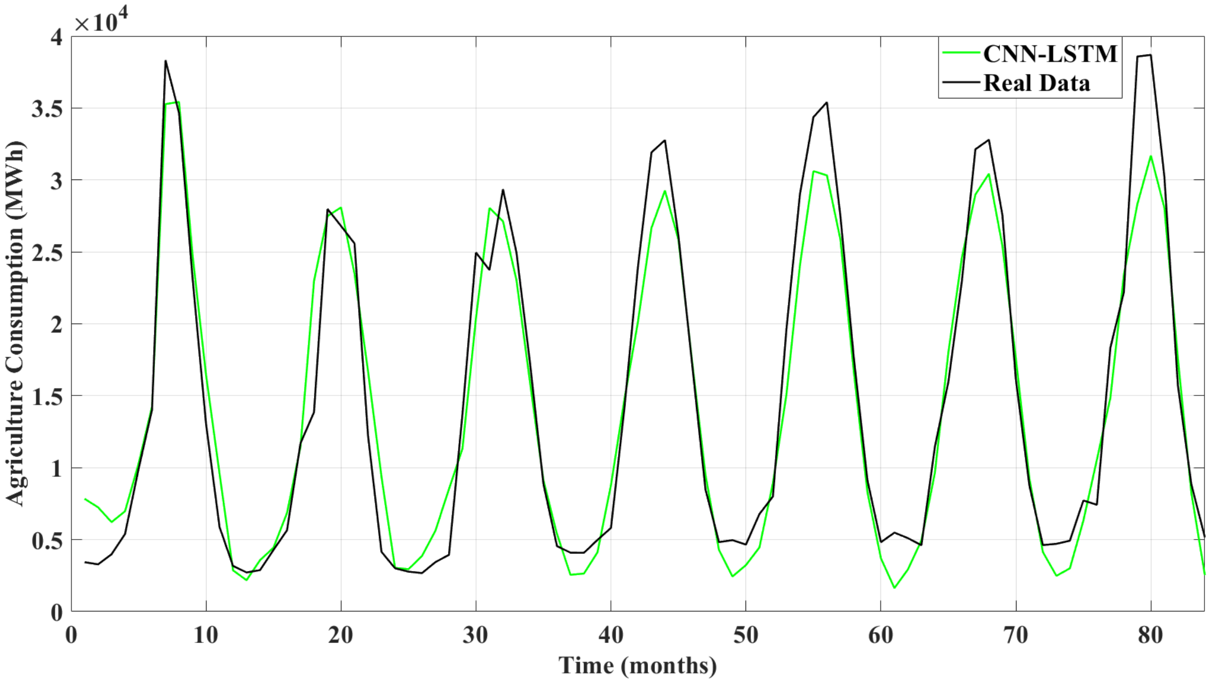


(b)



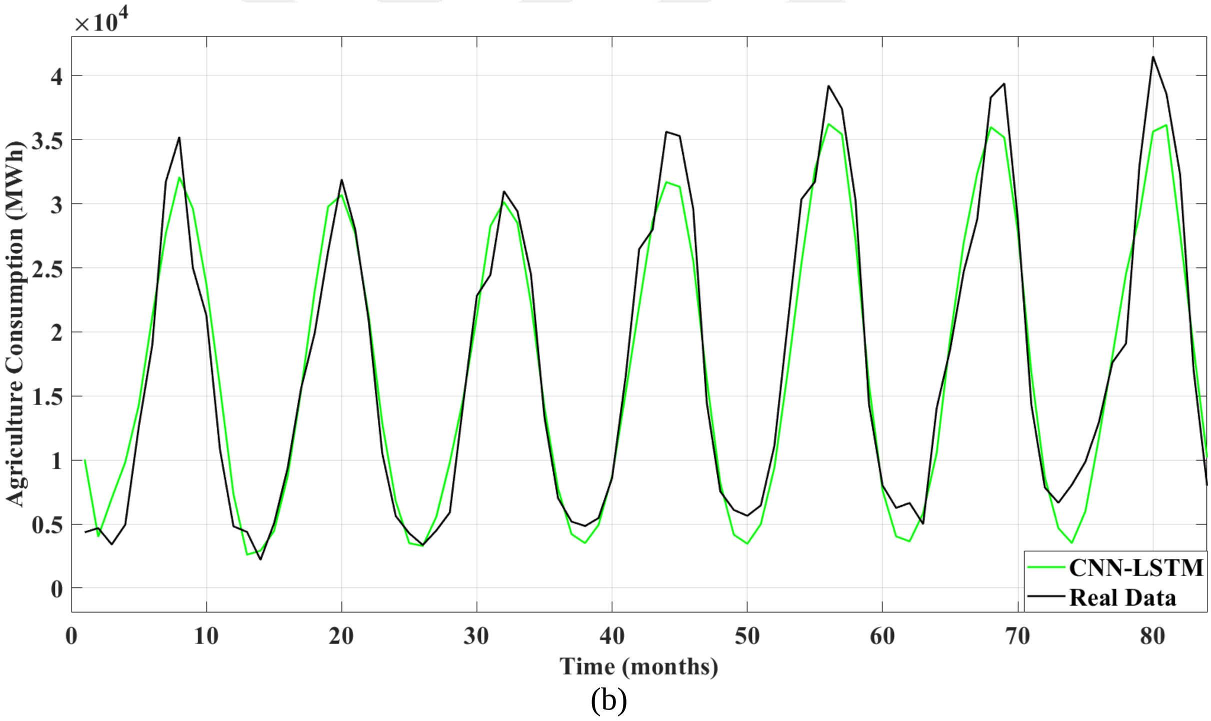
(c)

Figure 4.34. The CNN-LSTM model's forecast results for the industry load in (a) Adana, (b) Mersin, and (c) Antalya provinces.



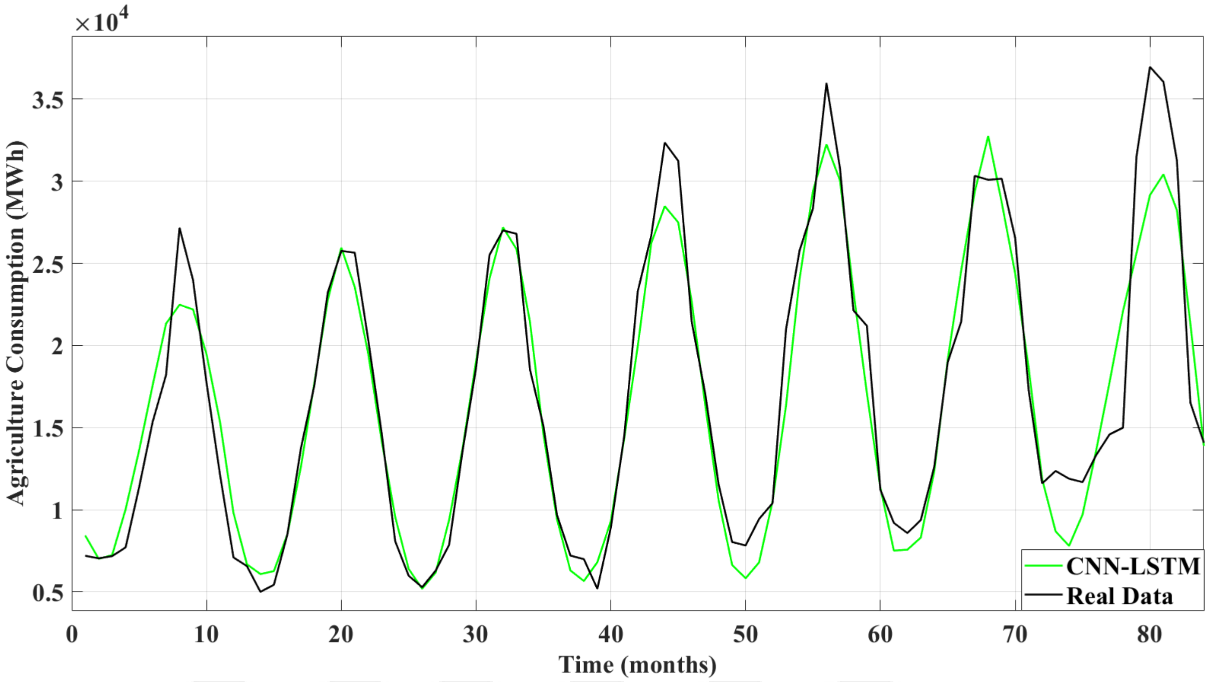
×10^4
CNN-LSTM
Real Data
Agriculture Consumption (MWh)
Time (months)

(a)



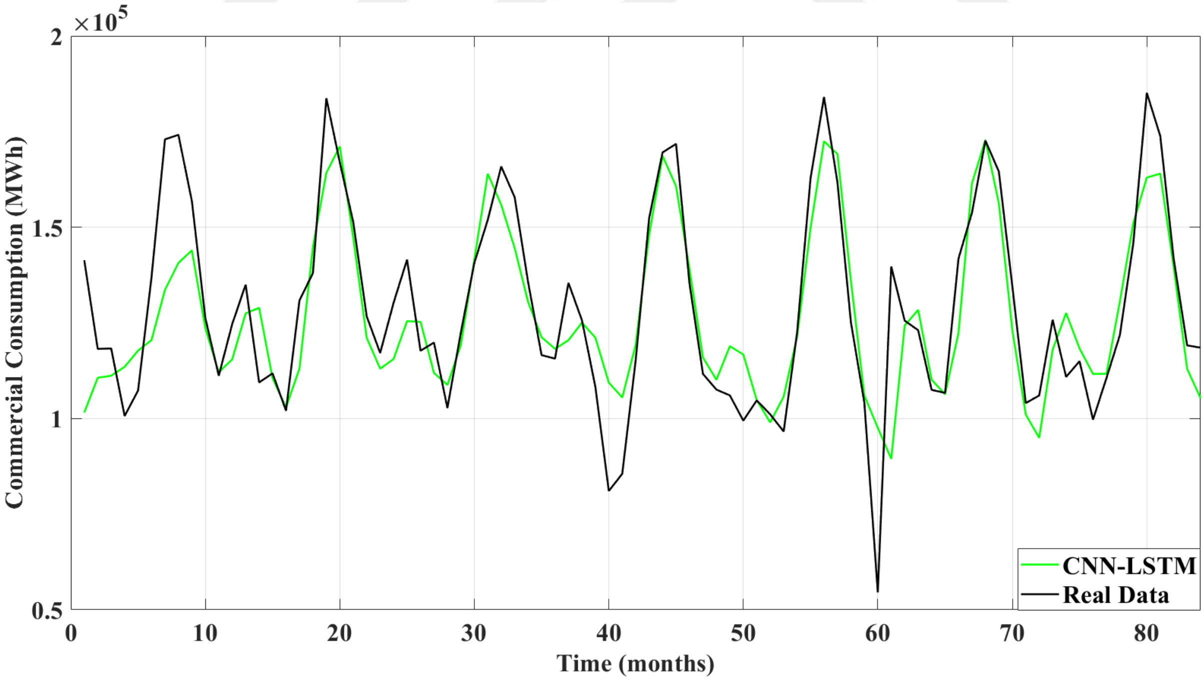
×10^4
CNN-LSTM
Real Data
Agriculture Consumption (MWh)
Time (months)

(b)

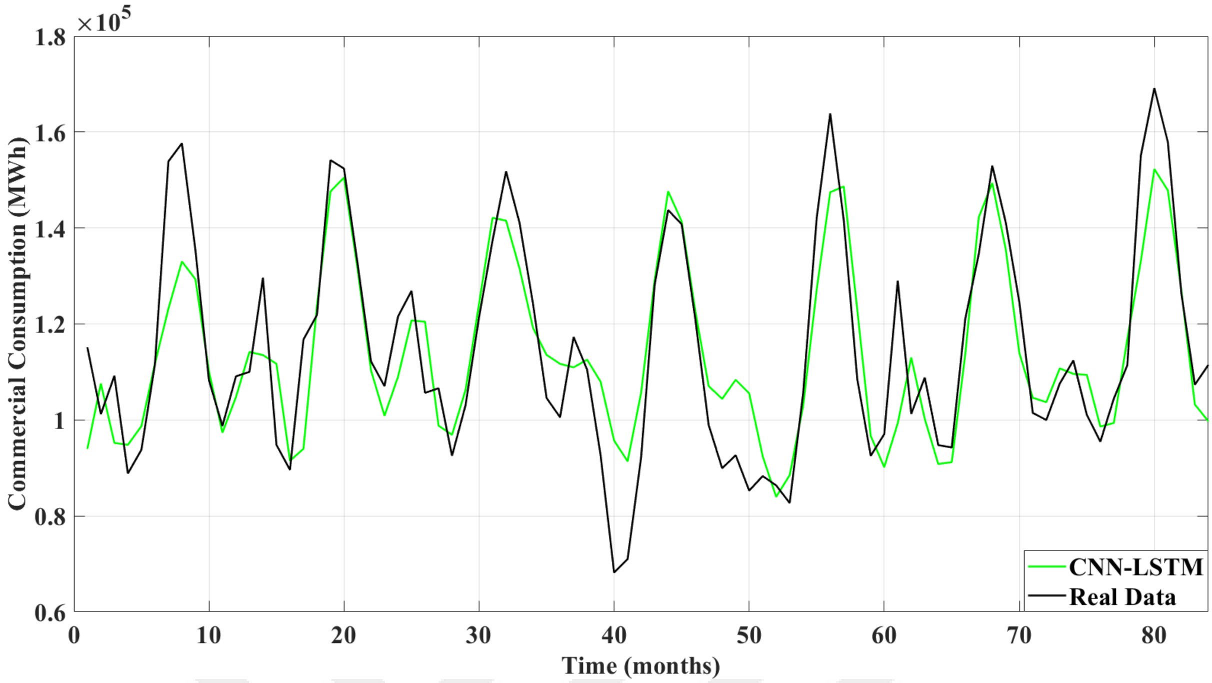


(c)

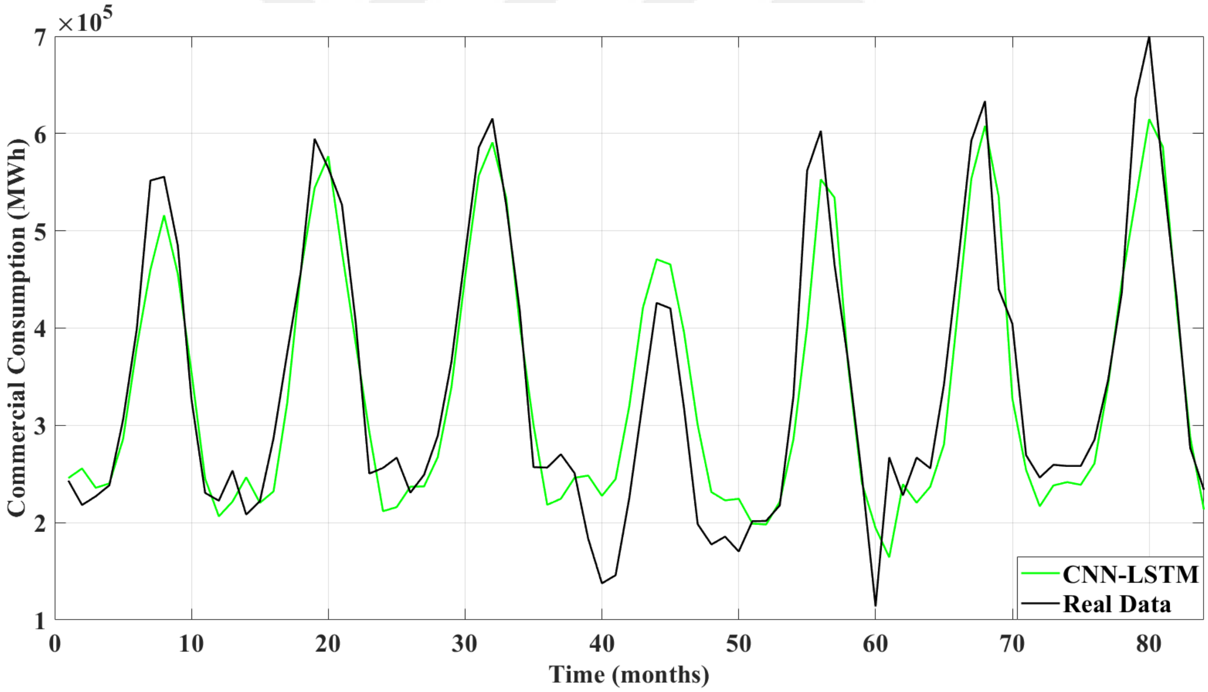
Figure 4.35. The CNN-LSTM model's forecast results for the agriculture load in (a) Adana, (b) Mersin, and (c) Antalya provinces.



(a)

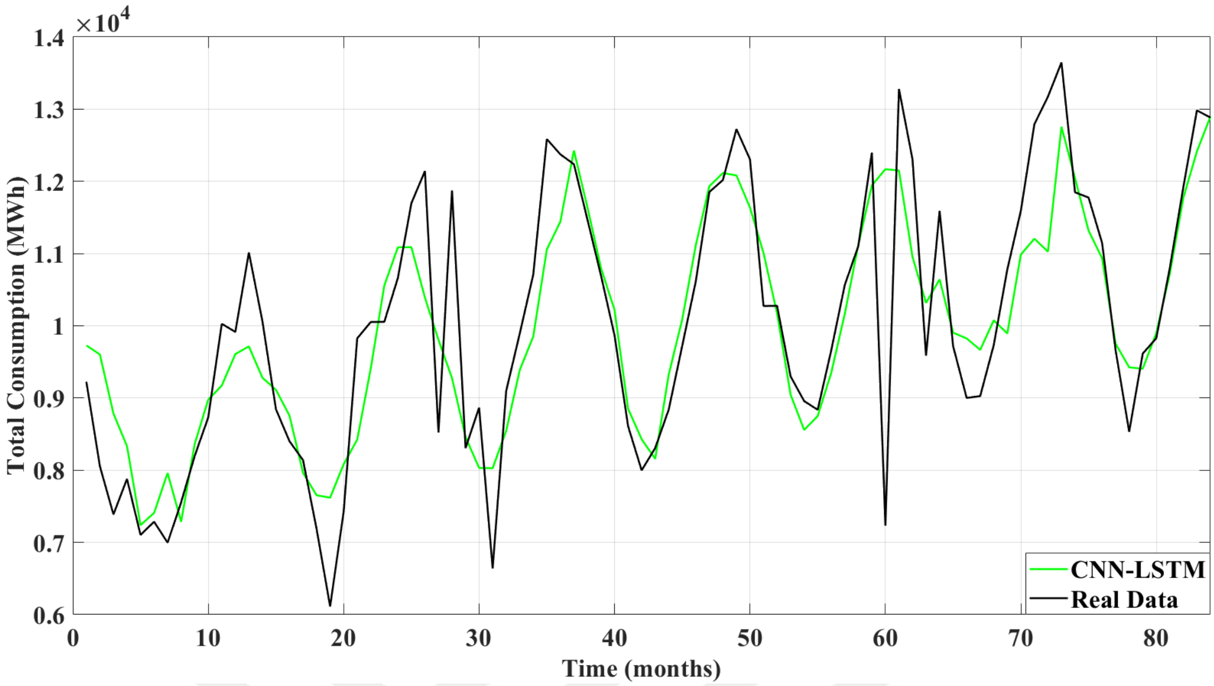


(b)



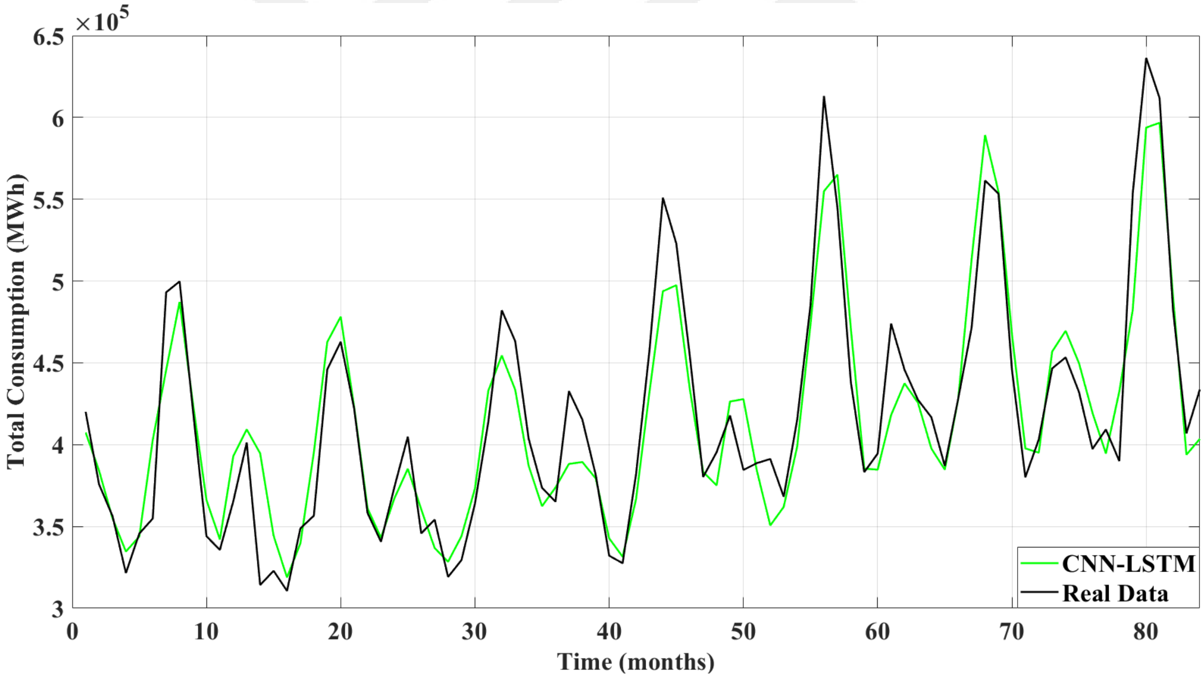
(c)

Figure 4.36. The CNN-LSTM model's forecast results for the commercial load in (a) Adana, (b) Mersin, and (c) Antalya provinces.



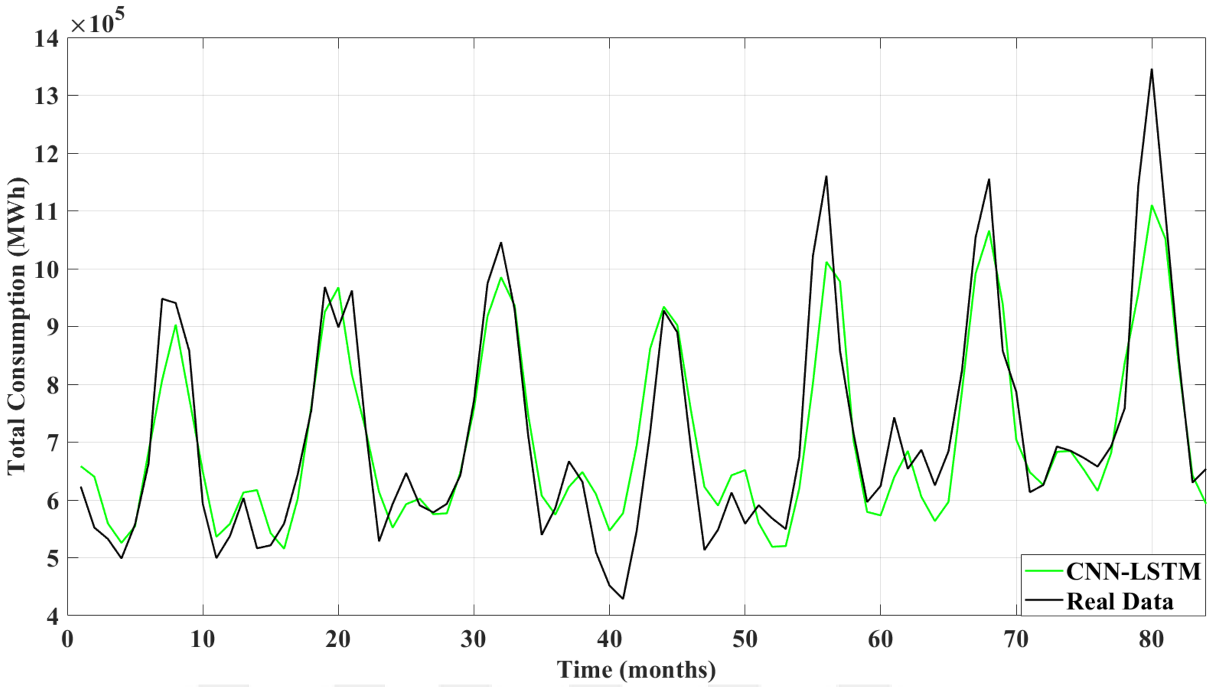
×10^4
Total Consumption (MWh)
Time (months)
CNN-LSTM
Real Data

(a)



×10^5
Total Consumption (MWh)
Time (months)
CNN-LSTM
Real Data

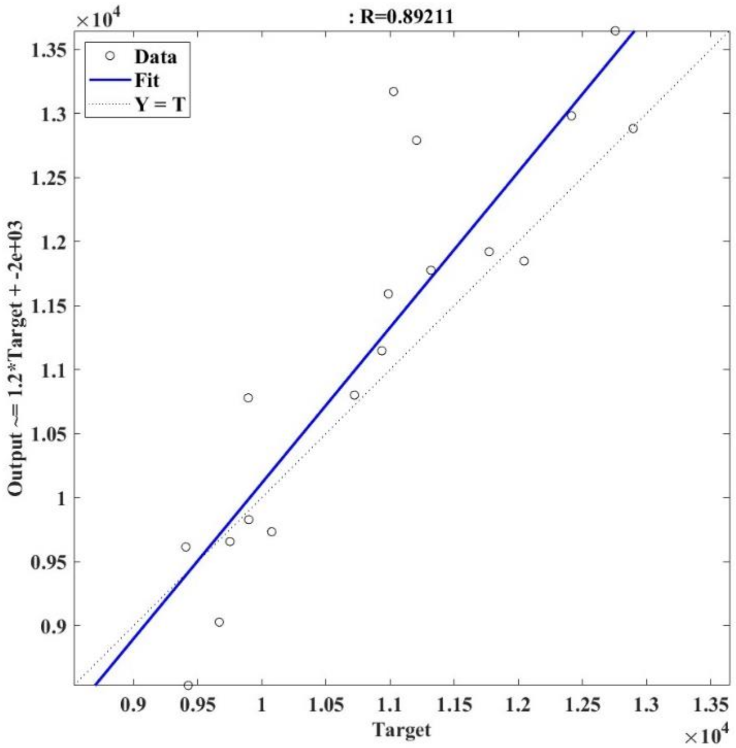
(b)



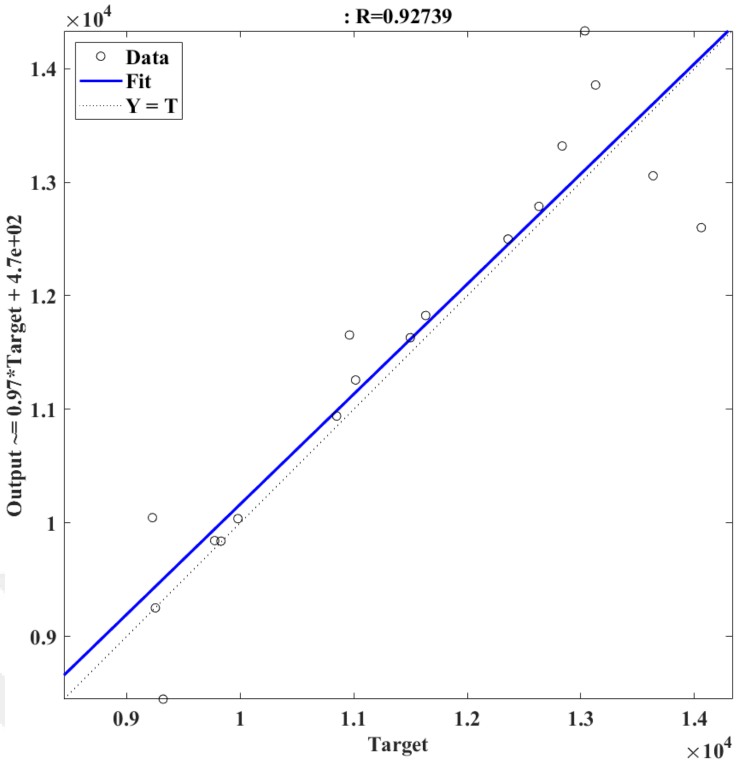
(c)

Figure 4.37. The CNN-LSTM model's forecast results for the total load in (a) Adana, (b) Mersin, and (c) Antalya provinces.

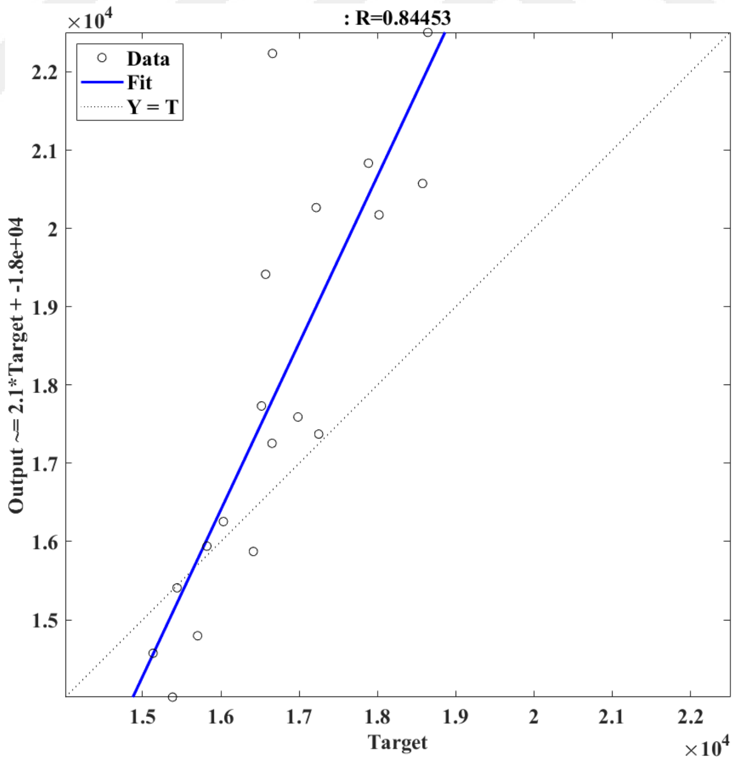
Figures 4.38 – 4.43 provide linear regression graphs of the CNN-LSTM model for the lighting, residential, commercial, and total load sectors for Adana, Mersin, and Antalya provinces.



(a)

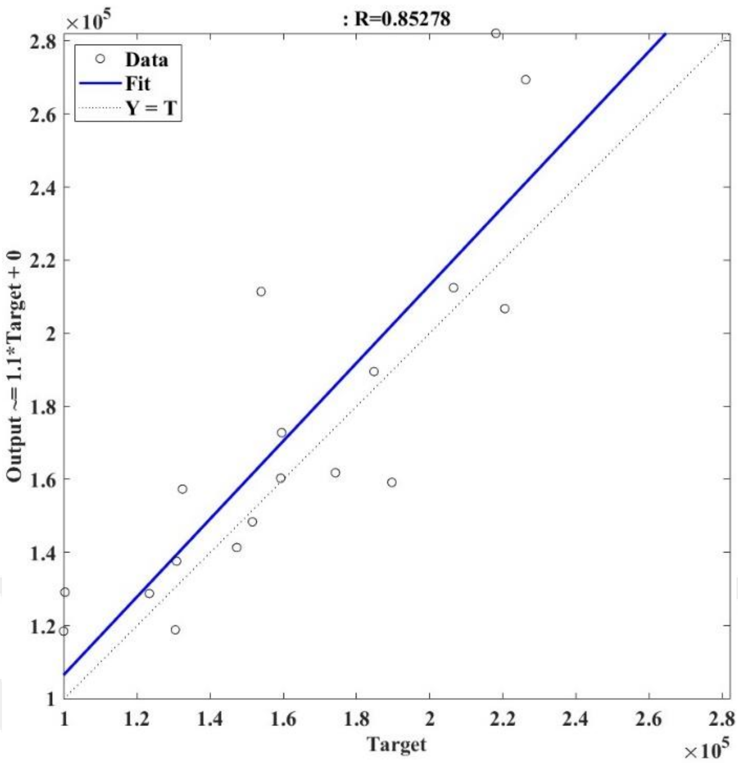


(b)



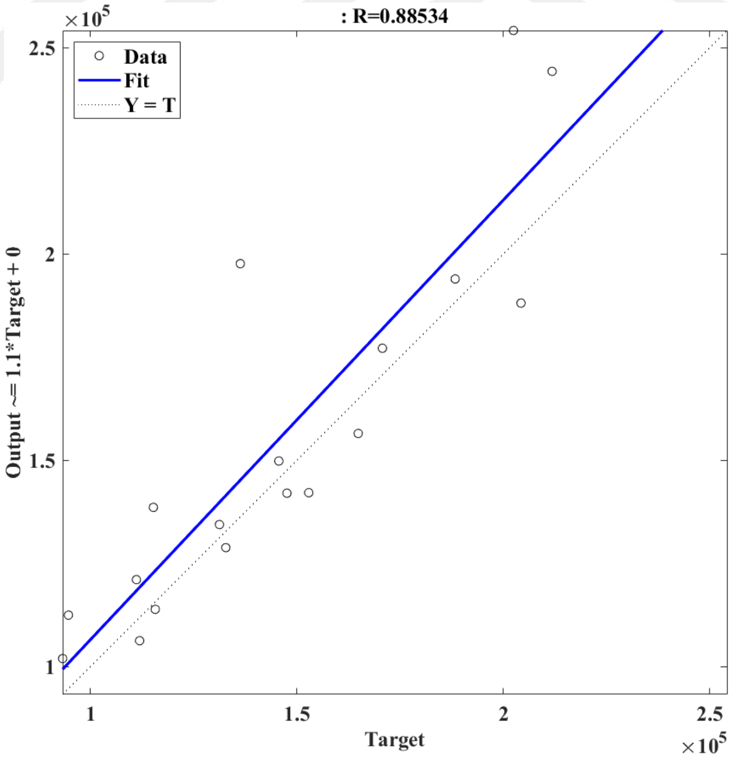
(c)

Figure 4.38. Linear regression graphs of the CNN-LSTM model for the lighting load in (a) Adana, (b) Mersin, and (c) Antalya provinces.



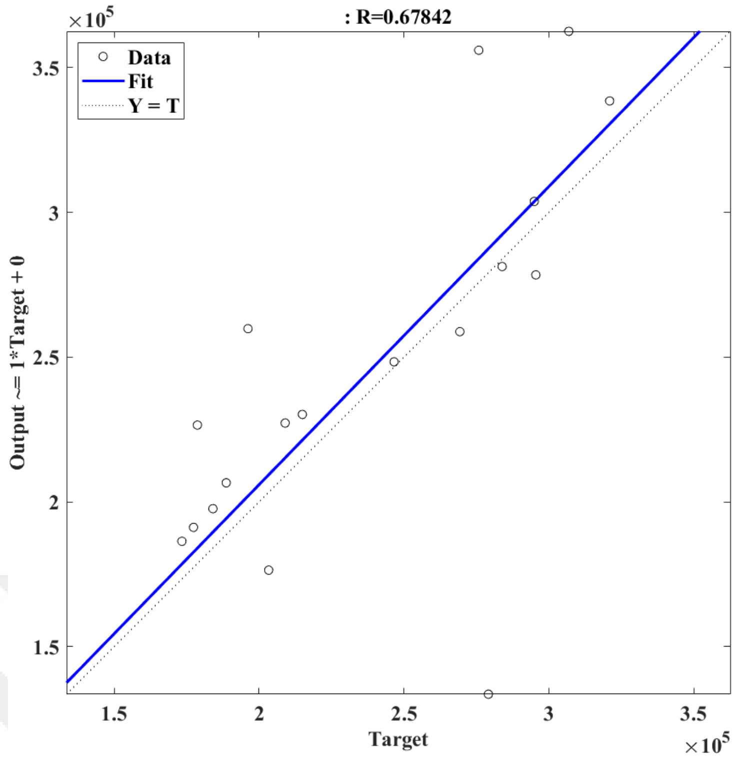
: R=0.85278
Data
Fit
Y = T
Output ~= 1.1*Target + 0
Target
×10^5

(a)



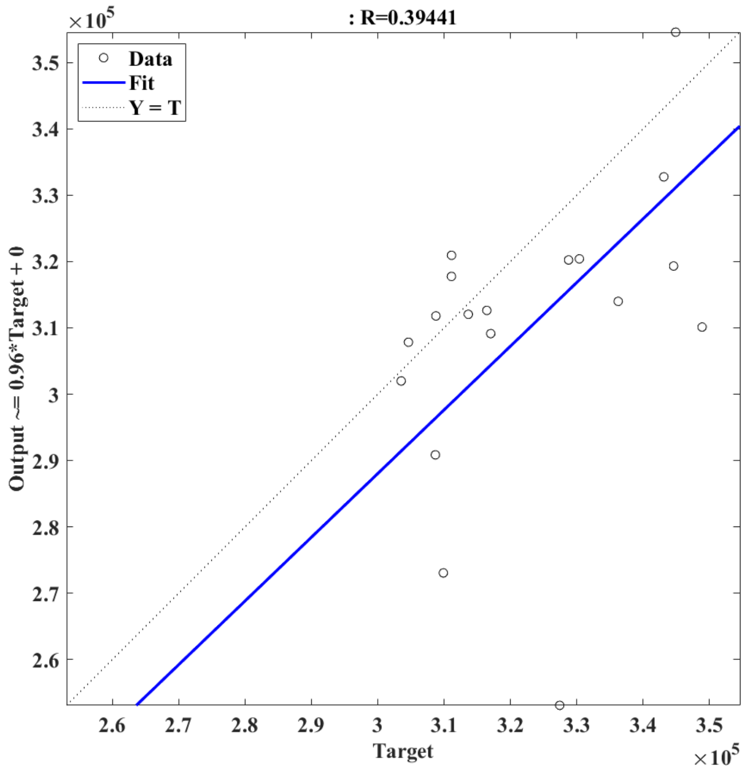
: R=0.88534
Data
Fit
Y = T
Output ~= 1.1*Target + 0
Target
×10^5

(b)

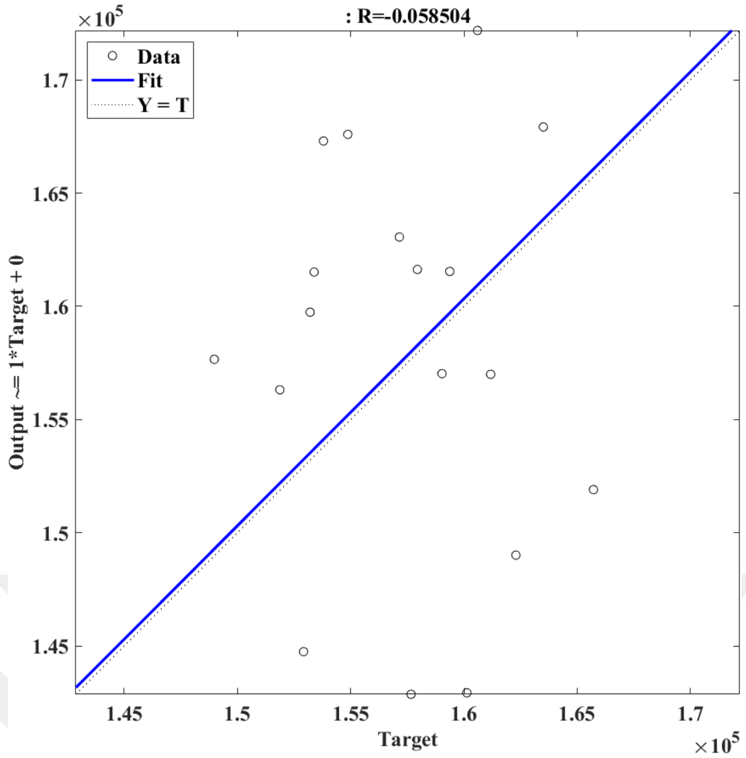


(c)

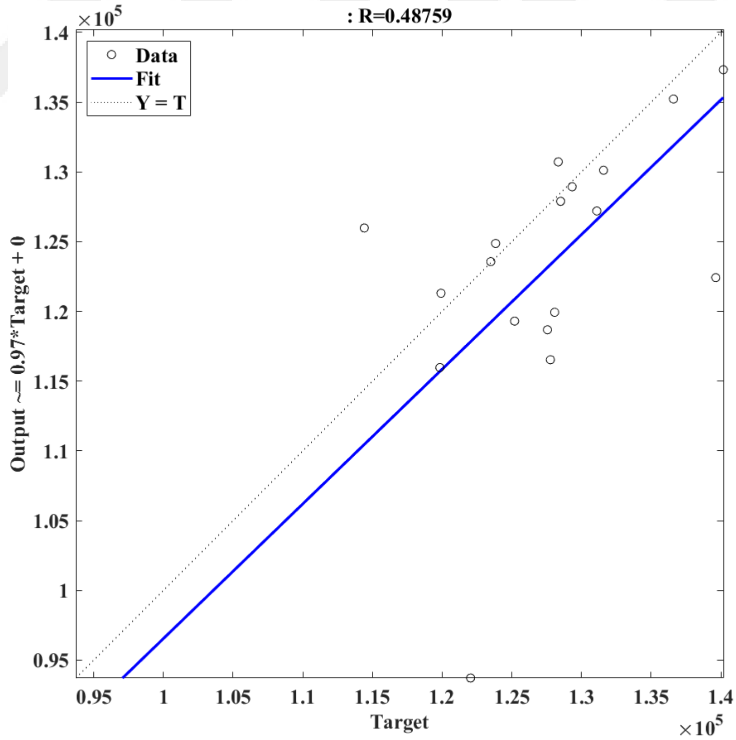
Figure 4.39. Linear regression graphs of the proposed CNN-LSTM model for the residential load in (a) Adana, (b) Mersin, and (c) Antalya provinces.



(a)

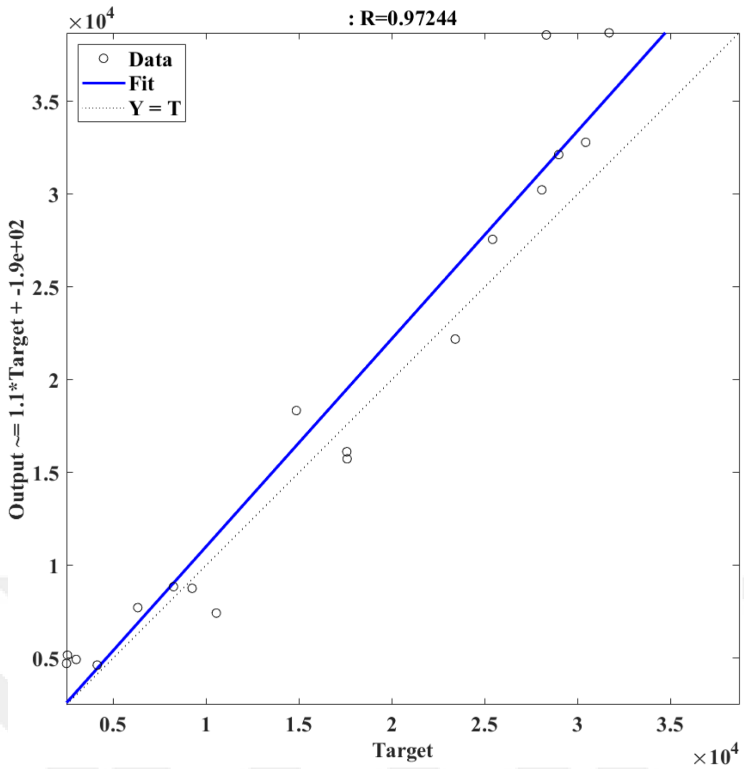


(b)

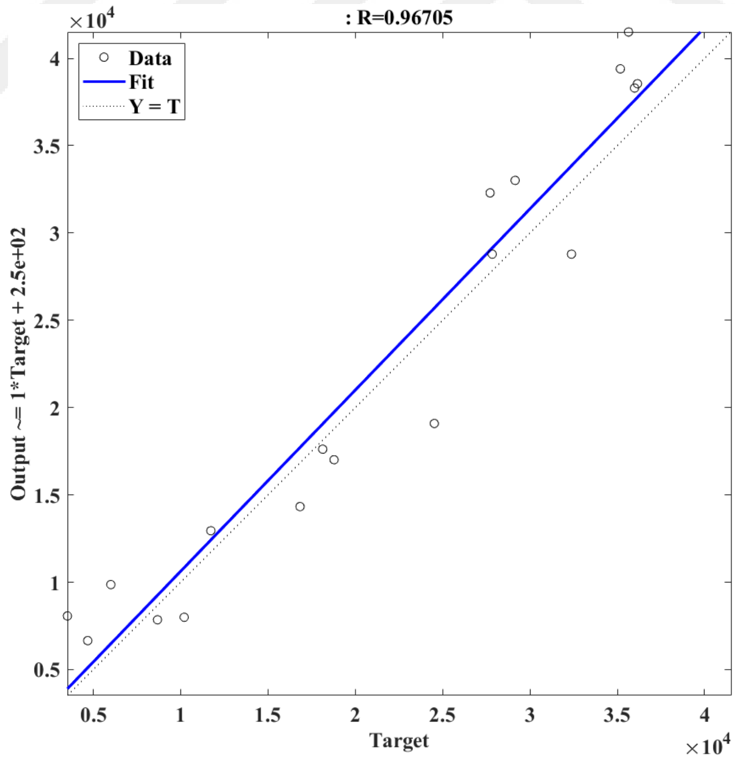


(c)

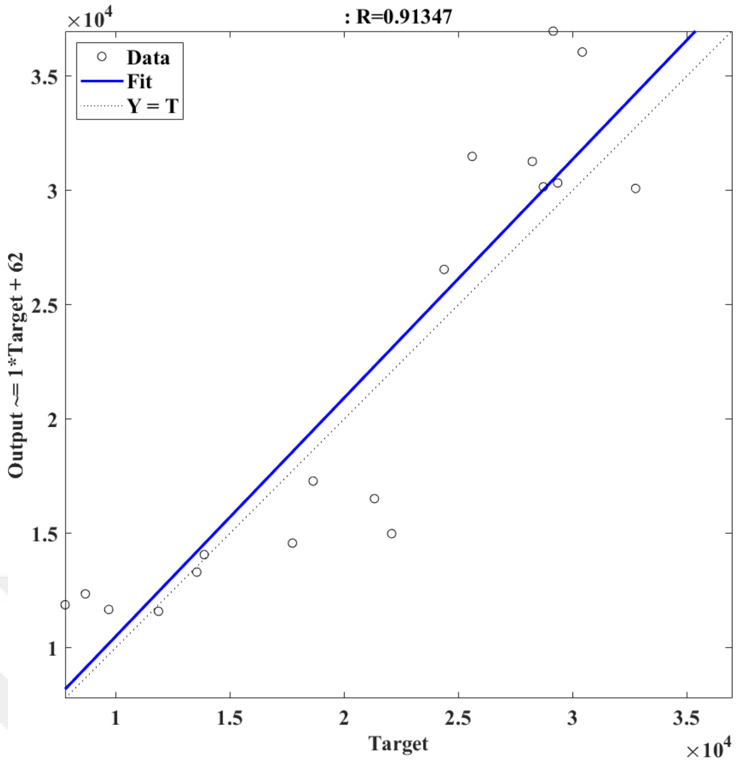
Figure 4.40. Linear regression graphs of the proposed CNN-LSTM model for the industry load in (a) Adana, (b) Mersin, and (c) Antalya provinces.


: R=0.97244
Data
Fit
Y = T
Output ~= 1.1*Target + -1.9e+02
Target

(a)

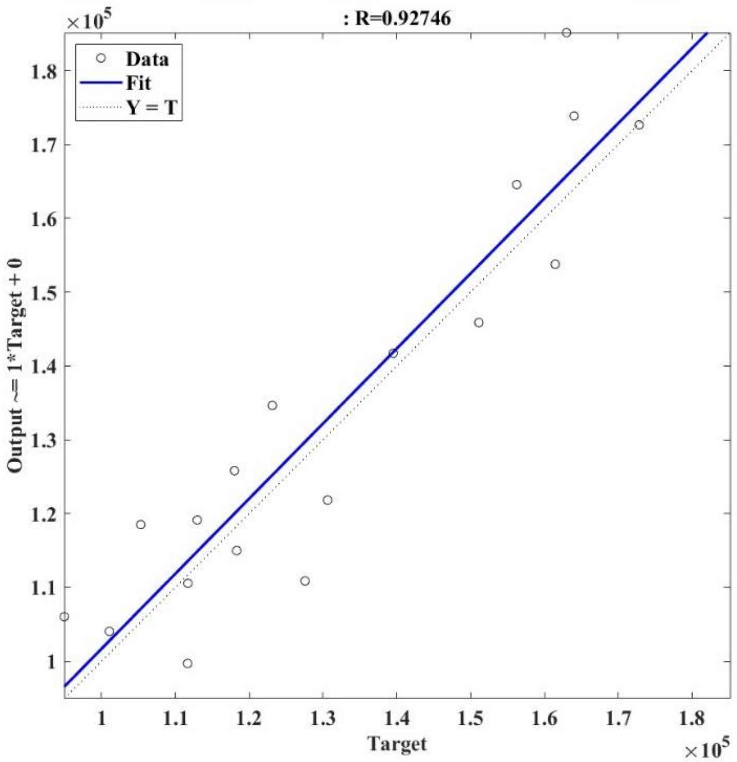

: R=0.96705
Data
Fit
Y = T
Output ~= 1*Target + 2.5e+02
Target

(b)

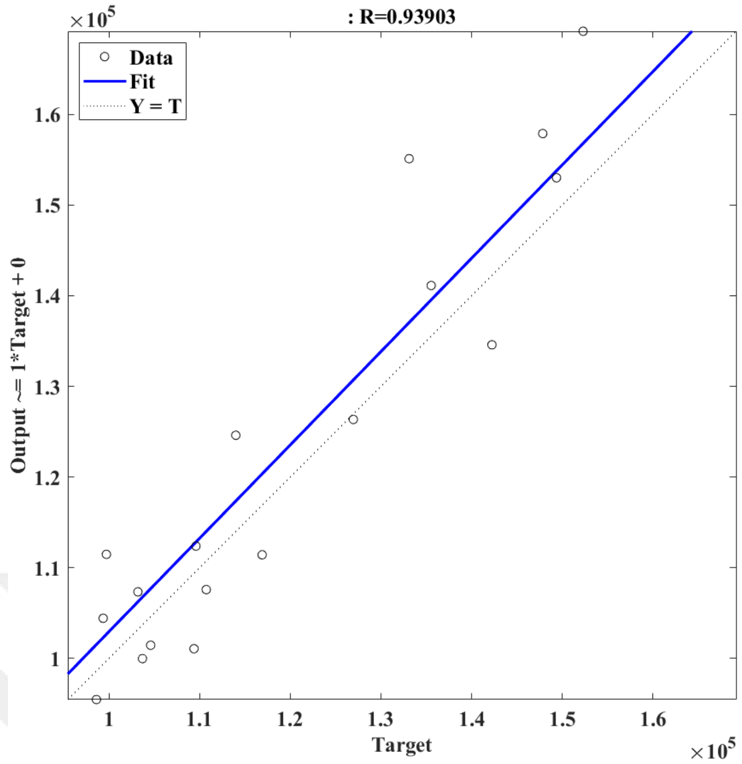


(c)

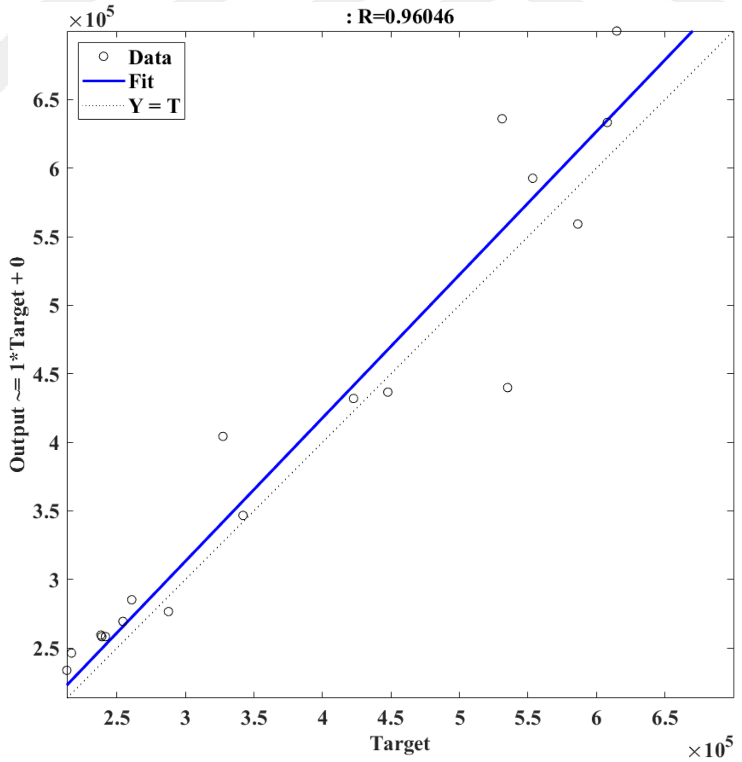
Figure 4.41. Linear regression graphs of the proposed CNN-LSTM model for the agriculture load in (a) Adana, (b) Mersin, and (c) Antalya provinces.



(a)

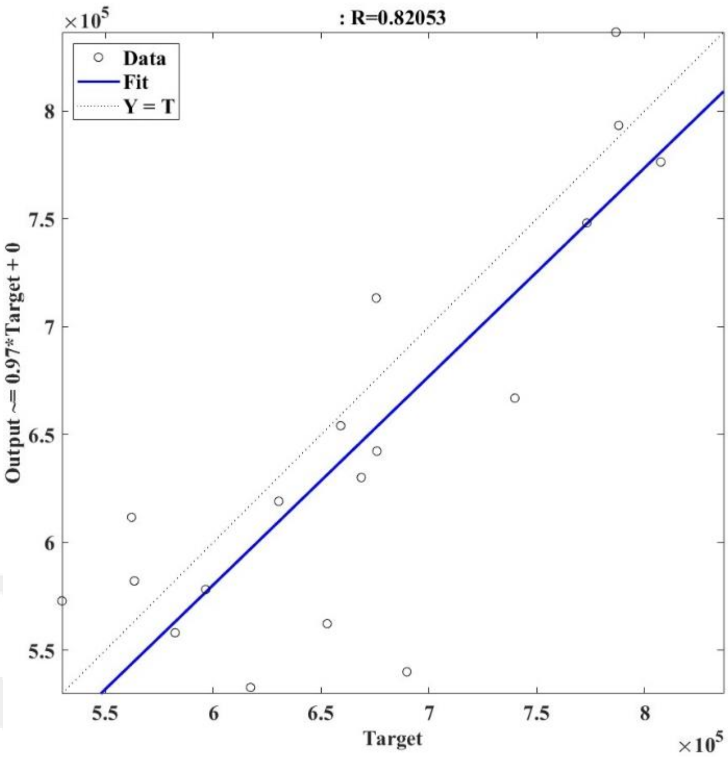


(b)

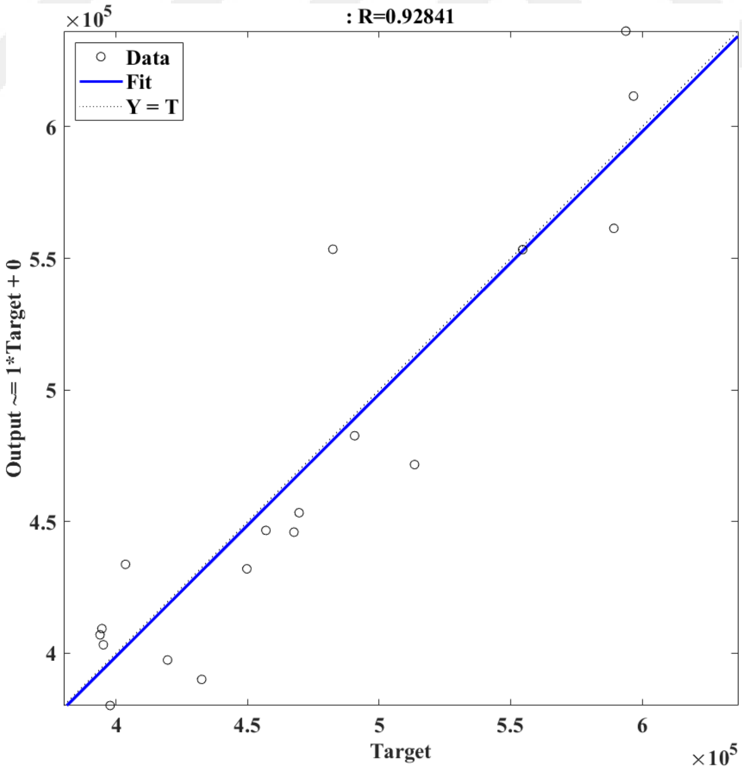


(c)

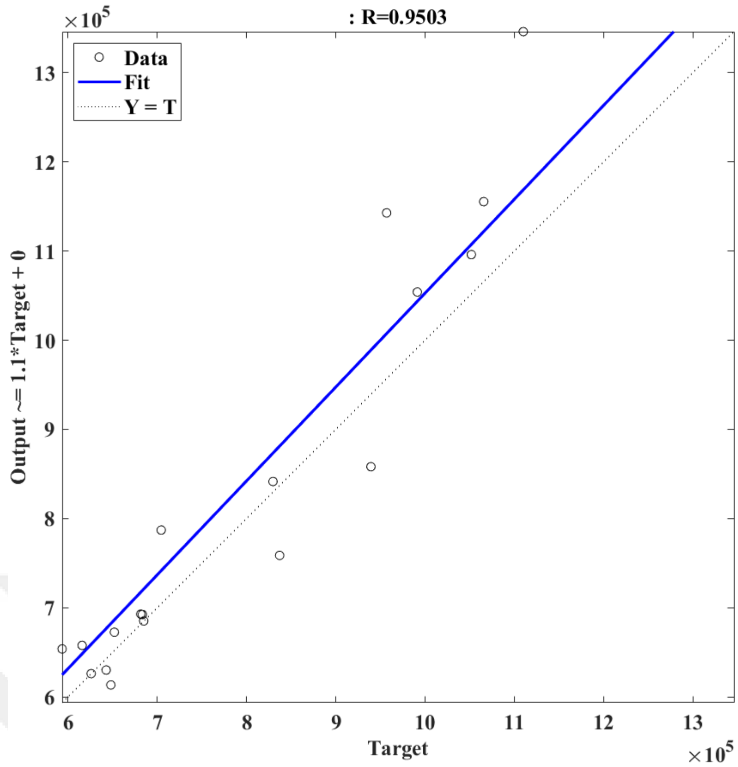
Figure 4.42. Linear regression graphs of the CNN-LSTM model for the commercial load in (a) Adana, (b) Mersin, and (c) Antalya provinces.


: R=0.82053
×10^5
Data
Fit
Y = T
Output ~= 0.97*Target + 0
8
7.5
7
6.5
6
5.5
5.5
6
6.5
7
7.5
8
Target
×10^5

(a)


: R=0.92841
×10^5
Data
Fit
Y = T
Output ~= 1*Target + 0
6
5.5
5
4.5
4
4
4.5
5
5.5
6
Target
×10^5

(b)



(c)

Figure 4.43. Linear regression graphs of the CNN-LSTM model for the total load in (a) Adana, (b) Mersin, and (c) Antalya provinces.

The results of the CNN-LSTM-based forecast have shown that such models often outperform standalone models by leveraging the strengths of both components. In this context, the CNN-LSTM model's superior performance is evident from the lower error metrics and closer alignment between predicted and actual values.

4.5. Comparison Results for Forecasting Models

Error metrics, which can also be known as performance or evaluation metrics, set the standard of performance measurement for a model or an algorithm's performance. These metrics help evaluate the accuracy of the model and point to the distance between what the model predicts and what is actual. RMSE measures the average magnitude of the error between predicted and observed values. It is obtained by squaring the errors before averaging, which gives more weight to more significant errors than to smaller ones. R^2 measures the proportion of the variance in the dependent variable that is predictable from the independent variables, indicating the goodness of fit of a model. MAPE is computed as the mean of the absolute percentage error between the forecasted and observed values. Therefore, it states the errors in the form of percentage errors. MAE measures the average magnitude of mistakes between the forecasted data and the corresponding actual values. It takes the average absolute differences between the predicted and actual values. These two metrics are commonly used in the assessment of regression model performance. RMSE and MAE give a scale of the errors in general, R^2 shows how well the model describes the variance in the data, and MAPE provides the error with a percentage independent of scale.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{4.1}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \tag{4.2}$$

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{4.3}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{4.4}$$

Where y_i is the actual values, $\hat{y}_i$ is the predicted values, n is the number of observations, $\bar{y}_i$ is the mean of actual values. The comparison of ELF results using CNN, LSTM, and CNN-LSTM models for sectoral loads in Adana, Mersin, and Antalya provinces demonstrates varying degrees of accuracy and regression performance across different load types. Tables 4.1.-4.9. present the RMSE, R^2, MAPE, and MAE results for the CNN, LSTM, and CNN-LSTM hybrid models.

Table 4.1. The RMSE, R^2, MAPE, and MAE results of the ELF using CNN in Adana province.

Load Types	***RMSE***	***R^2***	***MAPE***	***MAE***
Lighting load	3153,3386	0,3083106	6,2536702	6,9653290e+02
Residential load	32676,2852	0,8375292	4,2240462	6,5307559e+03
Commercial load	29628,6426	0,6827758	4,7077785	6,2172900e+03
Industry load	59663,6133	0,5052865	3,9056134	1,1689638e+04
Agriculture load	7309,5317	0,8927560	13,6913481	1,5923530e+03

Total load	200231,4688	-0,2186025	6,0193000	3,8797918e+04

Table 4.2. The RMSE, R^2, MAPE, and MAE results of the ELF using CNN in Mersin province.

Load Types	***RMSE***	R^2	***MAPE***	***MAE***
Lighting load	1550,9291	0,8600320	2,9371853	3,2454532e+02
Residential load	53612,7227	0,4968218	7,7377014	1,0588509e+04
Commercial load	26016,1133	0,6714156	4,3431625	5,4855806e+03
Industry load	25727,3438	0,6879432	3,5017781	5,2502314e+03
Agriculture load	7435,1743	0,8889938	10,0125771	1,7227791e+03
Total load	70951,2266	0,7715765	3,7508671	1,6704305e+04

Table 4.3. The RMSE, R^2, MAPE, and MAE results of the ELF using CNN in Antalya province.

Load Types	***RMSE***	R^2	***MAPE***	***MAE***
Lighting load	4435,1875	0,5522256	4,5924015	8,3204755e+02
Residential load	93458,8984	0,4047631	7,7886930	1,5936195e+04
Commercial load	136382,1406	0,7770480	8,0422935	2,8341816e+04
Industry load	13183,3672	0,8567232	2,4550807	0,8841809e+03
Agriculture load	5811,1108	0,9062234	5,8765659	1,1294353e+03
Total load	166906,1406	0,8259758	4,6407099	3,5068617e+04

Table 4.4. The RMSE, R^2, MAPE, and MAE results of the ELF using LSTM in Adana province.

Load Types	***RMSE***	R^2	***MAPE***	***MAE***
Lighting load	816,1257	0,6949797	7,2636762	6,9358685e+02
Residential load	26974,1953	0,7520037	8,4455404	1,3556314e+04
Commercial load	10322,8721	0,6984719	8,5820656	1,0292930e+04

Industry load	25335,9316	0,7030990	5,9651284	1,6432322e+04
Agriculture load	4497,3027	0,8896065	30,5696487	2,7504065e+03
Total load	57040,3789	0,7496395	5,4391284	3,2125727e+04

Table 4.5. The RMSE, R^2, MAPE, and MAE results of the ELF using LSTM in Mersin province.

Load Types	***RMSE***	***R^2***	***MAPE***	***MAE***
Lighting load	654,9219	0,8820130	5,4084330	5,2328186e+02
Residential load	22984,666	0,7844724	8,7680283	1,1769886e+04
Commercial load	9345,5605	0,7424074	7,8245707	8,7690264e+03
Industry load	9732,9961	0,7764751	6,1812716	8,3008223e+03
Agriculture load	3376,1777	0,9424170	19,4778366	2,2834526e+03
Total load	29700,416	0,8768755	4,5176053	1,9101965e+04

Table 4.6. The RMSE, R^2, MAPE, and MAE results of the ELF using LSTM in Antalya province.

Load Types	***RMSE***	***R^2***	***MAPE***	***MAE***
Lighting load	2237,8721	0,4312101	10,2930288	1,5115740e+03
Residential load	47708,2227	0,6592131	10,8840399	2,2684658e+04
Commercial load	47607,3047	0,8700338	13,4804745	3,9566805e+04
Industry load	9445,9814	0,8148286	5,5420885	5,8333057e+03
Agriculture load	3946,0127	0,9217494	11,7450218	1,8009873e+03
Total load	92478,9375	0,8278958	8,3074617	5,9026840e+04

Table 4.7. The RMSE, R^2, MAPE, and MAE results of the ELF using CNN-LSTM in Adana province.

Load Types	*RMSE*	R^2	*MAPE*	*MAE*
Lighting load	784,8497	0,7174536	6,9727435	6,6457367e+02
Residential load	26687,2188	0,7557703	8,5075474	1,3597542e+04
Commercial load	9992,8525	0,7001768	8,4300776	1,0188844e+04
Industry load	24084,4629	0,7109403	5,8854604	1,6264480e+04
Agriculture load	3545,8887	0,9285597	24,364189	2,2497725e+03
Total load	56273,8555	0,7515222	5,4229064	3,2103158e+04

Table 4.8. The RMSE, R^2, MAPE, and MAE results of the ELF using CNN-LSTM in Mersin province.

Load Types	*RMSE*	R^2	*MAPE*	*MAE*
Lighting load	623,5187	0,8879820	5,2009983	4,9254855e+02
Residential load	22557,7246	0,7879043	8,7012615	1,1670877e+04
Commercial load	8871,1572	0,7502817	7,8063021	8,6444512e+03
Industry load	9785,4404	0,7777996	6,1730299	8,3063271e+03
Agriculture load	3323,1958	0,9439582	19,4787598	2,2597283e+03
Total load	28675,9766	0,8703971	4,5925593	1,9424959e+04

Table 4.9. The RMSE, R^2, MAPE, and MAE results of the ELF using CNN-LSTM in Antalya province.

Load Types	*RMSE*	R^2	*MAPE*	*MAE*
Lighting load	2189,6477	0,4432346	10,5106878	1,5210759e+03
Residential load	47140,1992	0,6592131	10,8963575	2,3375863e+04
Commercial load	46985,6875	0,8747633	13,7533712	3,8836883e+04
Industry load	9398,252	0,8114871	5,5767093	5,8568428e+03

Agriculture load	3878,1665	0,9230694	11,4269714	1,7755262e+03
Total load	85409,6797	0,8376417	8,0522213	5,6931453e+04

The results of ELF using three different models for Adana province are as follows:

CNN Model

The lighting load has relatively high errors, indicating a lower prediction accuracy. The R^2 value of 0,3083106 shows a moderate fit. For the residential load, the performance is slightly better with an R^2 of 0,8375292. Commercial and industry loads show lower prediction accuracy with R^2 values of 0,6827758 and 0,5052865, respectively. Agriculture load is predicted with the highest accuracy among all load types, with an R^2 of 0,892756 and a very low RMSE (7309,5317). The total load shows a negative R^2 value, indicating poor model performance.

LSTM Model

Improvement is observed across most load types. For lighting load, the R^2 is 0,6949797 showing better model fit compared to CNN. The residential load prediction improves significantly. Commercial load shows a consistent R^2 value around 0,6984719, similar to CNN. The industry load prediction is moderately better with an R^2 of 0,703099. Agriculture load maintains high accuracy with an R^2 of 0,8896065. The total load shows better performance with an R^2 of 0,7496395.

CNN-LSTM Hybrid Model

This hybrid model yields further improvements. The lighting load R^2 increases to 0,7174536. The residential load shows the highest R^2 value among the three models at 0,7557703, with a significant reduction in RMSE. Commercial and industry loads maintain similar accuracy levels with slight improvements in R^2. Agriculture load achieves the highest R^2 at 0,9285597. The total load also shows improved performance (R^2: 0,7515222).

The results of ELF using three different models for Mersin province are as follows:

CNN Model

The lighting load prediction is quite accurate with an R^2 of 0,860032. The residential load has a lower R^2 of 0,4968218 and high MAPE. Commercial and industry loads show moderate accuracy with R^2 values around 0,6714156 and 0,6879432, respectively. Agriculture load is well predicted with an R^2 of 0,8889938. The total load has an R^2 of 0,7715765, indicating a good model fit.

LSTM Model

The lighting load R^2 improves to 0,882013. Residential load shows a significant increase in R^2 to 0,7844724. Commercial and industry loads continue to improve in accuracy with R^2 values of 0,7424074 and 0,7764751, respectively. Agriculture load achieves the highest R^2 at 0,942417. The total load R^2 increases to 0,8768755, indicating better overall performance.

CNN-LSTM Hybrid Model

Lighting load maintains high accuracy with an R^2 of 0,887982. Residential load shows further improvement with an R^2 of 0,7879043. Commercial and industry loads continue to improve in accuracy with R^2 values of 0,7502817 and 0,7777996, respectively. Agriculture load shows a slight increase in R^2 to 0,9439582. The total load R^2 is 0,8703971, showing the best overall model performance.

The results of ELF using three different models for Antalya province are as follows:

CNN Model

The lighting load prediction is less accurate with an R^2 of 0,5522256. Residential load has a lower R^2 of 0,4047631 and high MAPE. Commercial load shows a better fit with an R^2 of 0,777048. Industry and agriculture loads have higher accuracy with R^2 values of 0,8567232 and 0,9062234, respectively. The total load shows good performance with an R^2 of 0,8259758.

LSTM Model

The lighting load R^2 drops to 0,4312101. Residential load shows significant improvement in R^2 to 0,6592131. Commercial load achieves a high R^2 of 0,8700338. Industry and agriculture loads maintain high accuracy with R^2 values of 0,8148286 and 0,9217494, respectively. The total load shows good performance with an R^2 of 0,8278958.

CNN-LSTM hybrid Model

The lighting load maintains similar accuracy with an R^2 of 0,4432346. Residential load shows further improvement with an R^2 of 0,6592131. Commercial load achieves the highest R^2 among the three models at 0,8747633. Industry and agriculture loads maintain high accuracy with R^2

values of 0,8114871 and 0,9230694, respectively. The total load R^2 is 0,8376417, showing the best overall model performance.

Overall, the hybrid CNN-LSTM model outperforms the individual CNN and LSTM models across most load types and provinces. Agriculture load is consistently predicted with high accuracy across all models and provinces, indicating a more predictable pattern. Residential and commercial loads generally show higher errors, possibly due to more variable consumption patterns. The total load prediction accuracy improves significantly with the CNN-LSTM model, showcasing its capability to handle complex load patterns.

5. CONCLUSION

This thesis delves into ELF for Adana, Mersin, and Antalya provinces by utilizing advanced deep learning models such as LSTM, CNN, and CNN-LSTM hybrid models. Using monthly data from 2016 to 2023, the CNN-LSTM hybrid model can accurately capture consumption patterns across various sectors, including lighting, residential, industry, agriculture, commercial, and total load. The simulations conducted with Matlab/Simulink highlighted the crucial role of precise load forecasting in ensuring grid stability and effective energy management. The comparative analysis showed that while each deep learning model has its strengths, the hybrid CNN-LSTM model was particularly effective in capturing detailed load patterns. This research contributes to the field by demonstrating the potential of hybrid modeling approaches in developing sophisticated forecasting models that can adapt to changing consumption trends and significantly support sustainable energy planning. Future research should focus on refining these models by incorporating additional data such as weather patterns, economic indicators, and demographic changes, which can impact electricity demand. Furthermore, integrating real-time data and exploring advanced hybrid modeling techniques could improve predictive accuracy. Collaborations with utility companies could ensure that forecasting models are aligned with practical energy management needs, promoting their widespread adoption. Ultimately, future studies should aim to develop highly adaptive forecasting systems capable of quickly responding to changes in consumption trends, thus supporting sustainable energy management practices.

REFERENCES

Ageng, D., Huang, C.-Y., & Cheng, R.-G. (2021). A Short-Term Household Load Forecasting Framework Using LSTM and Data Preparation. *IEEE Access*, *9*, 167911–167919. https://doi.org/10.1109/ACCESS.2021.3133702

Agga, A., Abbou, A., Labbadi, M., & El Houm, Y. (2021). Short-Term Load Forecasting: Based on Hybrid CNN-LSTM Neural Network. *2021 6th International Conference on Power and Renewable Energy (ICPRE)*, 886–891. Shanghai, China: IEEE. https://doi.org/10.1109/ICPRE52634.2021.9635488

Agrawal, R. K., Muchahary, F., & Tripathi, M. M. (2018). Long term load forecasting with hourly predictions based on long-short-term-memory networks. *2018 IEEE Texas Power and Energy Conference (TPEC)*, 1–6. College Station, TX: IEEE. https://doi.org/10.1109/TPEC.2018.8312088

Aguilar Madrid, E., & Antonio, N. (2021). Short-Term Electricity Load Forecasting with Machine Learning. *Information*, *12*(2), 50. https://doi.org/10.3390/info12020050

Alhussein, M., Aurangzeb, K., & Haider, S. I. (2020). Hybrid CNN-LSTM Model for Short-Term Individual Household Load Forecasting. *IEEE Access*, *8*, 180544–180557. https://doi.org/10.1109/ACCESS.2020.3028281

Aslam, Shahzad, Ayub, N., Farooq, U., Alvi, M. J., Albogamy, F. R., Rukh, G., … Bukhsh, R. (2021). Towards Electric Price and Load Forecasting Using CNN-Based Ensembler in Smart Grid. *Sustainability*, *13*(22), 12653. https://doi.org/10.3390/su132212653

Aslam, Sheraz, Herodotou, H., Mohsin, S. M., Javaid, N., Ashraf, N., & Aslam, S. (2021). A survey on deep learning methods for power load and renewable energy forecasting in smart microgrids. *Renewable and Sustainable Energy Reviews*, *144*, 110992. https://doi.org/10.1016/j.rser.2021.110992

Azeem, A., Ismail, I., Jameel, S. M., & Harindran, V. R. (2021). Electrical Load Forecasting Models for Different Generation Modalities: A Review. *IEEE Access*, *9*, 142239–142263. https://doi.org/10.1109/ACCESS.2021.3120731

Bashiri Behmiri, N., Fezzi, C., & Ravazzolo, F. (2023). Incorporating air temperature into mid-term electricity load forecasting models using time-series regressions and neural networks. *Energy*, *278*, 127831. https://doi.org/10.1016/j.energy.2023.127831

Baur, L., Ditschuneit, K., Schambach, M., Kaymakci, C., Wollmann, T., & Sauer, A. (2024). Explainability and Interpretability in Electric Load Forecasting Using Machine Learning Techniques – A Review. *Energy and AI*, *16*, 100358. https://doi.org/10.1016/j.egyai.2024.100358

Bendaoud, N. M. M., Farah, N., & Ben Ahmed, S. (2021). Comparing Generative Adversarial Networks architectures for electricity demand forecasting. *Energy and Buildings*, *247*, 111152. https://doi.org/10.1016/j.enbuild.2021.111152

Bianchi, F. M., De Santis, E., Rizzi, A., & Sadeghian, A. (2015). Short-Term Electric Load Forecasting Using Echo State Networks and PCA Decomposition. *IEEE Access*, *3*, 1931–1943. https://doi.org/10.1109/ACCESS.2015.2485943

Bin Kamilin, M. H., & Yamaguchi, S. (2024). Resilient Electricity Load Forecasting Network with Collective Intelligence Predictor for Smart Cities. *Electronics*, *13*(4), 718. https://doi.org/10.3390/electronics13040718

Bouktif, S., Fiaz, A., Ouni, A., & Serhani, M. (2018). Optimal Deep Learning LSTM Model for Electric Load Forecasting using Feature Selection and Genetic Algorithm: Comparison with Machine Learning Approaches †. *Energies*, *11*(7), 1636. https://doi.org/10.3390/en11071636

Bouktif, S., Fiaz, A., Ouni, A., & Serhani, M. A. (2020). Multi-Sequence LSTM-RNN Deep Learning and Metaheuristics for Electric Load Forecasting. *Energies*, *13*(2), 391. https://doi.org/10.3390/en13020391

Ceperic, E., Ceperic, V., & Baric, A. (2013). A Strategy for Short-Term Load Forecasting by Support Vector Regression Machines. *IEEE Transactions on Power Systems*, *28*(4), 4356–4364. https://doi.org/10.1109/TPWRS.2013.2269803

Charytoniuk, W., & Chen, M.-S. (2000). Very short-term load forecasting using artificial neural networks. *IEEE Transactions on Power Systems*, *15*(1), 263–268. https://doi.org/10.1109/59.852131

Dedinec, A., Filiposka, S., Dedinec, A., & Kocarev, L. (2016). Deep belief network based electricity load forecasting: An analysis of Macedonian case. *Energy*, *115*, 1688–1700. https://doi.org/10.1016/j.energy.2016.07.090

Deihimi, A., & Showkati, H. (2012). Application of echo state networks in short-term electric load forecasting. *Energy*, *39*(1), 327–340. https://doi.org/10.1016/j.energy.2012.01.007

Dudek, G., Pelka, P., & Smyl, S. (2022). A Hybrid Residual Dilated LSTM and Exponential Smoothing Model for Midterm Electric Load Forecasting. *IEEE Transactions on Neural Networks and Learning Systems*, *33*(7), 2879–2891. https://doi.org/10.1109/TNNLS.2020.3046629

El-Azab, H.-A. I., Swief, R. A., El-Amary, N. H., & Temraz, H. K. (2024). Machine and deep learning approaches for forecasting electricity price and energy load assessment on real datasets. *Ain Shams Engineering Journal*, *15*(4), 102613. https://doi.org/10.1016/j.asej.2023.102613

Eren, Y., & Küçükdemiral, İ. (2024). A comprehensive review on deep learning approaches for short-term load forecasting. *Renewable and Sustainable Energy Reviews*, *189*, 114031. https://doi.org/10.1016/j.rser.2023.114031

Eskandari, H., Imani, M., & Moghaddam, M. P. (2021). Convolutional and recurrent neural network based model for short-term load forecasting. *Electric Power Systems Research*, *195*, 107173. https://doi.org/10.1016/j.epsr.2021.107173

Fan, G.-F., Liu, Y.-R., Wei, H.-Z., Yu, M., & Li, Y.-H. (2022). The new hybrid approaches to forecasting short-term electricity load. *Electric Power Systems Research*, *213*, 108759. https://doi.org/10.1016/j.epsr.2022.108759

Fan, G.-F., Yu, M., Dong, S.-Q., Yeh, Y.-H., & Hong, W.-C. (2021). Forecasting short-term electricity load using hybrid support vector regression with grey catastrophe and random forest modeling. *Utilities Policy*, *73*, 101294. https://doi.org/10.1016/j.jup.2021.101294

Feilat, E. A., & Bouzguenda, M. (2011). Medium-term load forecasting using neural network approach. *2011 IEEE PES Conference on Innovative Smart Grid Technologies - Middle East*, 1–5. Jeddah, Saudi Arabia: IEEE. https://doi.org/10.1109/ISGT-MidEast.2011.6220810

Gao, X., Li, X., Zhao, B., Ji, W., Jing, X., & He, Y. (2019). Short-Term Electricity Load Forecasting Model Based on EMD-GRU with Feature Selection. *Energies*, *12*(6), 1140. https://doi.org/10.3390/en12061140

Ghiassi, M., Zimbra, D. K., & Saidane, H. (2006). Medium term system load forecasting with a dynamic artificial neural network model. *Electric Power Systems Research*, *76*(5), 302–316. https://doi.org/10.1016/j.epsr.2005.06.010

Ghimire, S., Deo, R. C., Casillas-Pérez, D., & Salcedo-Sanz, S. (2024). Two-step deep learning framework with error compensation technique for short-term, half-hourly electricity price forecasting. *Applied Energy*, *353*, 122059. https://doi.org/10.1016/j.apenergy.2023.122059

Gu, L., Wang, J., & Liu, J. (2024). A combined system based on data preprocessing and optimization algorithm for electricity load forecasting. *Computers & Industrial Engineering*, *191*, 110114. https://doi.org/10.1016/j.cie.2024.110114

Guan, C., Luh, P. B., Michel, L. D., Wang, Y., & Friedland, P. B. (2013). Very Short-Term Load Forecasting: Wavelet Neural Networks With Data Pre-Filtering. *IEEE Transactions on Power Systems*, *28*(1), 30–41. https://doi.org/10.1109/TPWRS.2012.2197639

Gul, M. J., Urfa, G. M., Paul, A., Moon, J., Rho, S., & Hwang, E. (2021). Mid-term electricity load prediction using CNN and Bi-LSTM. *The Journal of Supercomputing*, *77*(10), 10942–10958. https://doi.org/10.1007/s11227-021-03686-8

Guo, W., Che, L., Shahidehpour, M., & Wan, X. (2021). Machine-Learning based methods in short-term load forecasting. *The Electricity Journal*, *34*(1), 106884. https://doi.org/10.1016/j.tej.2020.106884

Guo, X., Zhao, Q., Zheng, D., Ning, Y., & Gao, Y. (2020). A short-term load forecasting model of multi-scale CNN-LSTM hybrid neural network considering the real-time electricity price. *Energy Reports*, *6*, 1046–1053. https://doi.org/10.1016/j.egyr.2020.11.078

Haque, A., & Rahman, S. (2022). Short-term electrical load forecasting through heuristic configuration of regularized deep neural network. *Applied Soft Computing*, *122*, 108877. https://doi.org/10.1016/j.asoc.2022.108877

He, Y., Deng, J., & Li, H. (2017). Short-Term Power Load Forecasting with Deep Belief Network and Copula Models. *2017 9th International Conference on Intelligent Human-Machine Systems and Cybernetics (IHMSC)*, 191–194. Hangzhou: IEEE. https://doi.org/10.1109/IHMSC.2017.50

Hippert, H. S., Pedreira, C. E., & Souza, R. C. (2001). Neural networks for short-term load forecasting: A review and evaluation. *IEEE Transactions on Power Systems*, *16*(1), 44–55. https://doi.org/10.1109/59.910780

Hong, T., Wilson, J., & Xie, J. (2014). Long Term Probabilistic Load Forecasting and Normalization With Hourly Information. *IEEE Transactions on Smart Grid*, *5*(1), 456–462. https://doi.org/10.1109/TSG.2013.2274373

Hu, Y., Li, J., Hong, M., Ren, J., & Man, Y. (2022). Industrial artificial intelligence based energy management system: Integrated framework for electricity load forecasting and fault prediction. *Energy*, *244*, 123195. https://doi.org/10.1016/j.energy.2022.123195

Huy, P. C., Minh, N. Q., Tien, N. D., & Anh, T. T. Q. (2022). Short-Term Electricity Load Forecasting Based on Temporal Fusion Transformer Model. *IEEE Access*, *10*, 106296–106304. https://doi.org/10.1109/ACCESS.2022.3211941

Imani, M. (2021). Electrical load-temperature CNN for residential load forecasting. *Energy*, *227*, 120480. https://doi.org/10.1016/j.energy.2021.120480

Jawad, M., Nadeem, M. S. A., Shim, S.-O., Khan, I. R., Shaheen, A., Habib, N., … Aziz, W. (2020). Machine Learning Based Cost Effective Electricity Load Forecasting Model Using Correlated Meteorological Parameters. *IEEE Access*, *8*, 146847–146864. https://doi.org/10.1109/ACCESS.2020.3014086

Jin, H., Guo, J., Tang, L., & Du, P. (2024). Long-term electricity demand forecasting under low-carbon energy transition: Based on the bidirectional feedback between power demand and generation mix. *Energy*, *286*, 129435. https://doi.org/10.1016/j.energy.2023.129435

Jung, S.-M., Park, S., Jung, S.-W., & Hwang, E. (2020). Monthly Electric Load Forecasting Using Transfer Learning for Smart Cities. *Sustainability*, *12*(16), 6364. https://doi.org/10.3390/su12166364

Kaur, A., Nonnenmacher, L., & Coimbra, C. F. M. (2016). Net load forecasting for high renewable energy penetration grids. *Energy*, *114*, 1073–1084. https://doi.org/10.1016/j.energy.2016.08.067

Khan, G. M., Khattak, A. R., Zafari, F., & Mahmud, S. A. (2013). Electrical load forecasting using fast learning recurrent neural networks. *The 2013 International Joint Conference on Neural Networks (IJCNN)*, 1–6. Dallas, TX, USA: IEEE. https://doi.org/10.1109/IJCNN.2013.6706998

Khan, S., Javaid, N., Chand, A., Khan, A. B. M., Rashid, F., & Afridi, I. U. (2019). Electricity Load Forecasting for Each Day of Week Using Deep CNN. In L. Barolli, M. Takizawa, F. Xhafa, & T. Enokido (Eds.), *Web, Artificial Intelligence and Network Applications* (pp. 1107–

1119). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-030-15035-8_107

Khan, Z. A., Ullah, A., Ul Haq, I., Hamdy, M., Maria Mauro, G., Muhammad, K., … Baik, S. W. (2022). Efficient Short-Term Electricity Load Forecasting for Effective Energy Management. *Sustainable Energy Technologies and Assessments*, *53*, 102337. https://doi.org/10.1016/j.seta.2022.102337

Kong, W., Dong, Z. Y., Jia, Y., Hill, D. J., Xu, Y., & Zhang, Y. (2019). Short-Term Residential Load Forecasting Based on LSTM Recurrent Neural Network. *IEEE Transactions on Smart Grid*, *10*(1), 841–851. https://doi.org/10.1109/TSG.2017.2753802

Kong, X., Li, C., Zheng, F., & Wang, C. (2020). Improved Deep Belief Network for Short-Term Load Forecasting Considering Demand-Side Management. *IEEE Transactions on Power Systems*, *35*(2), 1531–1538. https://doi.org/10.1109/TPWRS.2019.2943972

Kottath, R., Singh, P., & Bhowmick, A. (2023). Swarm-based hybrid optimization algorithms: An exhaustive analysis and its applications to electricity load and price forecasting. *Soft Computing*, *27*(19), 14095–14126. https://doi.org/10.1007/s00500-023-07928-0

Krichen, M. (2023). Convolutional Neural Networks: A Survey. *Computers*, *12*(8), 151. https://doi.org/10.3390/computers12080151

Kumar, S., Hussain, L., Banarjee, S., & Reza, M. (2018). Energy Load Forecasting using Deep Learning Approach-LSTM and GRU in Spark Cluster. *2018 Fifth International Conference on Emerging Applications of Information Technology (EAIT)*, 1–4. Kolkata: IEEE. https://doi.org/10.1109/EAIT.2018.8470406

Kwabena Patrick, M., Felix Adekoya, A., Abra Mighty, A., & Edward, B. Y. (2022). Capsule Networks – A survey. *Journal of King Saud University - Computer and Information Sciences*, *34*(1), 1295–1310. https://doi.org/10.1016/j.jksuci.2019.09.014

Kwon, B.-S., Park, R.-J., & Song, K.-B. (2020). Short-Term Load Forecasting Based on Deep Neural Networks Using LSTM Layer. *Journal of Electrical Engineering & Technology*, *15*(4), 1501–1509. https://doi.org/10.1007/s42835-020-00424-7

Lee, J., & Cho, Y. (2022). National-scale electricity peak load forecasting: Traditional, machine learning, or hybrid model? *Energy*, *239*, 122366. https://doi.org/10.1016/j.energy.2021.122366

L'Heureux, A., Grolinger, K., & Capretz, M. A. M. (2022). Transformer-Based Model for Electrical Load Forecasting. *Energies*, *15*(14), 4993. https://doi.org/10.3390/en15144993

Li, J., Deng, D., Zhao, J., Cai, D., Hu, W., Zhang, M., & Huang, Q. (2021). A Novel Hybrid Short-Term Load Forecasting Method of Smart Grid Using MLR and LSTM Neural Network. *IEEE Transactions on Industrial Informatics*, *17*(4), 2443–2452. https://doi.org/10.1109/TII.2020.3000184

Li, L., Ota, K., & Dong, M. (2017). Everything is Image: CNN-based Short-Term Electrical Load Forecasting for Smart Grid. *2017 14th International Symposium on Pervasive Systems, Algorithms and Networks & 2017 11th International Conference on Frontier of Computer Science and Technology & 2017 Third International Symposium of Creative Computing (ISPAN-FCST-ISCC)*, 344–351. Exeter: IEEE. https://doi.org/10.1109/ISPAN-FCST-ISCC.2017.78

Li, S., Goel, L., & Wang, P. (2016). An ensemble approach for short-term load forecasting by extreme learning machine. *Applied Energy*, *170*, 22–29. https://doi.org/10.1016/j.apenergy.2016.02.114

Lin, J., Ma, J., Zhu, J., & Cui, Y. (2022). Short-term load forecasting based on LSTM networks considering attention mechanism. *International Journal of Electrical Power & Energy Systems*, *137*, 107818. https://doi.org/10.1016/j.ijepes.2021.107818

Lindberg, K. B., Seljom, P., Madsen, H., Fischer, D., & Korpås, M. (2019). Long-term electricity load forecasting: Current and future trends. *Utilities Policy*, *58*, 102–119. https://doi.org/10.1016/j.jup.2019.04.001

Liu, H., Chen, L., & Shi, X. (2023). Short-Term Electricity Load Forecasting Based on Back Propagation Neural Network Considering Key Meteorological Factors. *2023 6th International Conference on Electrical Engineering and Green Energy (CEEGE)*, 260–263. Grimstad, Norway: IEEE. https://doi.org/10.1109/CEEGE58447.2023.10246523

Liu, P., Zheng, P., & Chen, Z. (2019). Deep Learning with Stacked Denoising Auto-Encoder for Short-Term Electric Load Forecasting. *Energies*, *12*(12), 2445. https://doi.org/10.3390/en12122445

Luo, J., Hong, T., Gao, Z., & Fang, S.-C. (2023). A robust support vector regression model for electric load forecasting. *International Journal of Forecasting*, *39*(2), 1005–1020. https://doi.org/10.1016/j.ijforecast.2022.04.001

Mamun, A. A., Sohel, Md., Mohammad, N., Haque Sunny, Md. S., Dipta, D. R., & Hossain, E. (2020). A Comprehensive Review of the Load Forecasting Techniques Using Single and Hybrid Predictive Models. *IEEE Access*, *8*, 134911–134939. https://doi.org/10.1109/ACCESS.2020.3010702

Matrenin, P., Safaraliev, M., Dmitriev, S., Kokin, S., Ghulomzoda, A., & Mitrofanov, S. (2022). Medium-term load forecasting in isolated power systems based on ensemble machine learning models. *Energy Reports*, *8*, 612–618. https://doi.org/10.1016/j.egyr.2021.11.175

Memarzadeh, G., & Keynia, F. (2021). Short-term electricity load and price forecasting by a new optimal LSTM-NN based prediction algorithm. *Electric Power Systems Research*, *192*, 106995. https://doi.org/10.1016/j.epsr.2020.106995

Monjazeb, M. R., Amiri, H., & Movahedi, A. (2024). Wholesale electricity price forecasting by Quantile Regression and Kalman Filter method. *Energy*, *290*, 129925. https://doi.org/10.1016/j.energy.2023.129925

Mujeeb, S., Javaid, N., Ilahi, M., Wadud, Z., Ishmanov, F., & Afzal, M. (2019). Deep Long Short-Term Memory: A New Price and Load Forecasting Scheme for Big Data in Smart Cities. *Sustainability*, *11*(4), 987. https://doi.org/10.3390/su11040987

Muzaffar, S., & Afshari, A. (2019). Short-Term Load Forecasts Using LSTM Networks. *Energy Procedia*, *158*, 2922–2927. https://doi.org/10.1016/j.egypro.2019.01.952

Nie, Y., Li, P., Wang, J., & Zhang, L. (2024). A novel multivariate electrical price bi-forecasting system based on deep learning, a multi-input multi-output structure and an operator combination mechanism. *Applied Energy*, *366*, 123233. https://doi.org/10.1016/j.apenergy.2024.123233

Niu, D., Yu, M., Sun, L., Gao, T., & Wang, K. (2022). Short-term multi-energy load forecasting for integrated energy systems based on CNN-BiGRU optimized by attention mechanism. *Applied Energy*, *313*, 118801. https://doi.org/10.1016/j.apenergy.2022.118801

Nti, I. K., Teimeh, M., Nyarko-Boateng, O., & Adekoya, A. F. (2020). Electricity load forecasting: A systematic review. *Journal of Electrical Systems and Information Technology*, *7*(1), 13. https://doi.org/10.1186/s43067-020-00021-8

Prasetyo, B. S., Adytia, D., & Aditya, I. A. (2023). Time Series Forecasting of Electricity Load Using Hybrid CNN-BiLSTM with an Attention Approach: A Case Study in Bali, Indonesia. *2023 International Conference on Data Science and Its Applications (ICoDSA)*, 460–464. Bandung, Indonesia: IEEE. https://doi.org/10.1109/ICoDSA58501.2023.10277176

Randall, L., Agrawal, P., & Mohapatra, A. (2023). IoT Based Load Forecasting for Reliable Integration of Renewable Energy Sources. *Journal of Signal Processing Systems*, *95*(11), 1341–1352. https://doi.org/10.1007/s11265-022-01785-0

Ren, C., Jia, L., & Wang, Z. (2021). A CNN-LSTM Hybrid Model Based Short-term Power Load Forecasting. *2021 Power System and Green Energy Conference (PSGEC)*, 182–186. Shanghai, China: IEEE. https://doi.org/10.1109/PSGEC51302.2021.9542404

Republic of Türkiye Energy Market Regulatory (EMRA). Electricity Market Monthly Sector Report List, https://www.epdk.gov.tr/Detay/Icerik/3-0-23/elektrikaylik-sektor-raporlar, Accessed: 01 March 2024.

Ribeiro, G. T., Mariani, V. C., & Coelho, L. D. S. (2019). Enhanced ensemble structures using wavelet neural networks applied to short-term load forecasting. *Engineering Applications of Artificial Intelligence*, *82*, 272–281. https://doi.org/10.1016/j.engappai.2019.03.012

Rubasinghe, O., Zhang, X., Chau, T. K., Chow, Y. H., Fernando, T., & Iu, H. H.-C. (2024). A Novel Sequence to Sequence Data Modelling Based CNN-LSTM Algorithm for Three Years Ahead Monthly Peak Load Forecasting. *IEEE Transactions on Power Systems*, *39*(1), 1932–1947. https://doi.org/10.1109/TPWRS.2023.3271325

Saglam, M., Lv, X., Spataru, C., & Karaman, O. A. (2024). Instantaneous Electricity Peak Load Forecasting Using Optimization and Machine Learning. *Energies*, *17*(4), 777. https://doi.org/10.3390/en17040777

Sajjad, M., Khan, Z. A., Ullah, A., Hussain, T., Ullah, W., Lee, M. Y., & Baik, S. W. (2020). A Novel CNN-GRU-Based Hybrid Approach for Short-Term Residential Load Forecasting. *IEEE Access*, *8*, 143759–143768. https://doi.org/10.1109/ACCESS.2020.3009537

Sehovac, L., & Grolinger, K. (2020). Deep Learning for Load Forecasting: Sequence to Sequence Recurrent Neural Networks With Attention. *IEEE Access*, *8*, 36411–36426. https://doi.org/10.1109/ACCESS.2020.2975738

Sekhar, C., & Dahiya, R. (2023). Robust framework based on hybrid deep learning approach for short term load forecasting of building electricity demand. *Energy*, *268*, 126660. https://doi.org/10.1016/j.energy.2023.126660

Sharma, S., Agrawal, R. K., & Tripathi, M. M. (2020). Synergism of Recurrent Neural Network and Fuzzy Logic for Short Term Energy Load Forecasting. *2020 Fourth International Conference on Computing Methodologies and Communication (ICCMC)*, 165–169. Erode, India: IEEE. https://doi.org/10.1109/ICCMC48092.2020.ICCMC-00033

Shi, H., Wang, L., Scherer, R., Wozniak, M., Zhang, P., & Wei, W. (2021). Short-Term Load Forecasting Based on Adabelief Optimized Temporal Convolutional Network and Gated Recurrent Unit Hybrid Neural Network. *IEEE Access*, *9*, 66965–66981. https://doi.org/10.1109/ACCESS.2021.3076313

Shirzadi, N., Nizami, A., Khazen, M., & Nik-Bakht, M. (2021). Medium-Term Regional Electricity Load Forecasting through Machine Learning and Deep Learning. *Designs*, *5*(2), 27. https://doi.org/10.3390/designs5020027

Sun, L., Lin, Y., Pan, N., Fu, Q., Chen, L., & Yang, J. (2023). Demand-Side Electricity Load Forecasting Based on Time-Series Decomposition Combined with Kernel Extreme Learning Machine Improved by Sparrow Algorithm. *Energies*, *16*(23), 7714. https://doi.org/10.3390/en16237714

Tang, X., Chen, H., Xiang, W., Yang, J., & Zou, M. (2022). Short-Term Load Forecasting Using Channel and Temporal Attention Based Temporal Convolutional Network. *Electric Power Systems Research*, *205*, 107761. https://doi.org/10.1016/j.epsr.2021.107761

Tang, X., Dai, Y., Liu, Q., Dang, X., & Xu, J. (2019a). Application of Bidirectional Recurrent Neural Network Combined With Deep Belief Network in Short-Term Load Forecasting. *IEEE Access*, *7*, 160660–160670. https://doi.org/10.1109/ACCESS.2019.2950957

Tang, X., Dai, Y., Wang, T., & Chen, Y. (2019b). Short-term power load forecasting based on multi-layer bidirectional recurrent neural network. *IET Generation, Transmission & Distribution*, *13*(17), 3847–3854. https://doi.org/10.1049/iet-gtd.2018.6687

Tong, C., Li, J., Lang, C., Kong, F., Niu, J., & Rodrigues, J. J. P. C. (2018). An efficient deep model for day-ahead electricity load forecasting with stacked denoising auto-encoders. *Journal of Parallel and Distributed Computing*, *117*, 267–273. https://doi.org/10.1016/j.jpdc.2017.06.007

Tudose, A. M., Sidea, D. O., Picioroaga, I. I., Boicea, V. A., & Bulac, C. (2020). A CNN Based Model for Short-Term Load Forecasting: A Real Case Study on the Romanian Power System. *2020 55th International Universities Power Engineering Conference (UPEC)*, 1–6. Torino, Italy: IEEE. https://doi.org/10.1109/UPEC49904.2020.9209768

Wan, A., Chang, Q., AL-Bukhaiti, K., & He, J. (2023). Short-term power load forecasting for combined heat and power using CNN-LSTM enhanced by attention mechanism. *Energy*, *282*, 128274. https://doi.org/10.1016/j.energy.2023.128274

Wang, C., Wang, Y., Ding, Z., Zheng, T., Hu, J., & Zhang, K. (2022). A Transformer-Based Method of Multienergy Load Forecasting in Integrated Energy System. *IEEE Transactions on Smart Grid*, *13*(4), 2703–2714. https://doi.org/10.1109/TSG.2022.3166600

Wang, D., Gan, J., Mao, J., Chen, F., & Yu, L. (2023). Forecasting power demand in China with a CNN-LSTM model including multimodal information. *Energy*, *263*, 126012. https://doi.org/10.1016/j.energy.2022.126012

Wang, K., Zhang, J., Li, X., & Zhang, Y. (2023). Long-Term Power Load Forecasting Using LSTM-Informer with Ensemble Learning. *Electronics*, *12*(10), 2175. https://doi.org/10.3390/electronics12102175

Wang, S., Wang, S., & Wang, D. (2019). Combined probability density model for medium term load forecasting based on quantile regression and kernel density estimation. *Energy Procedia*, *158*, 6446–6451. https://doi.org/10.1016/j.egypro.2019.01.169

Wen, Z., Xie, L., Fan, Q., & Feng, H. (2020). Long term electric load forecasting based on TS-type recurrent fuzzy neural network model. *Electric Power Systems Research*, *179*, 106106. https://doi.org/10.1016/j.epsr.2019.106106

Wu, K., Wu, J., Feng, L., Yang, B., Liang, R., Yang, S., & Zhao, R. (2021). An attention-based CNN-LSTM-BiLSTM model for short-term electric load forecasting in integrated energy system. *International Transactions on Electrical Energy Systems*, *31*(1). https://doi.org/10.1002/2050-7038.12637

Xian, J., Meng, A., & Fu, J. (2024). Short-Term Load Probability Prediction Based on Conditional Generative Adversarial Network Curve Generation. *IEEE Access*, *12*, 64165–64176. https://doi.org/10.1109/ACCESS.2024.3395659

Yamasaki, M., Freire, R. Z., Seman, L. O., Stefenon, S. F., Mariani, V. C., & Dos Santos Coelho, L. (2024). Optimized hybrid ensemble learning approaches applied to very short-term load forecasting. *International Journal of Electrical Power & Energy Systems*, *155*, 109579. https://doi.org/10.1016/j.ijepes.2023.109579

Yazici, I., Beyca, O. F., & Delen, D. (2022). Deep-learning-based short-term electricity load forecasting: A real case application. *Engineering Applications of Artificial Intelligence*, *109*, 104645. https://doi.org/10.1016/j.engappai.2021.104645

Yıldız, C. (2023). An integrated model based on deep kernel extreme learning machine and variational mode decomposition for day-ahead electricity load forecasting. *Neural Computing and Applications*, *35*(25), 18763–18781. https://doi.org/10.1007/s00521-023-08702-x

Zang, H., Xu, R., Cheng, L., Ding, T., Liu, L., Wei, Z., & Sun, G. (2021). Residential load forecasting based on LSTM fusing self-attention mechanism with pooling. *Energy*, *229*, 120682. https://doi.org/10.1016/j.energy.2021.120682

Zhang, G., Bai, X., & Wang, Y. (2021). Short-time multi-energy load forecasting method based on CNN-Seq2Seq model with attention mechanism. *Machine Learning with Applications*, *5*, 100064. https://doi.org/10.1016/j.mlwa.2021.100064

Zhang, J., Wei, Y.-M., Li, D., Tan, Z., & Zhou, J. (2018). Short term electricity load forecasting using a hybrid model. *Energy*, *158*, 774–781. https://doi.org/10.1016/j.energy.2018.06.012

Zhang, R., Dong, Z. Y., Xu, Y., Meng, K., & Wong, K. P. (2013). Short-term load forecasting of Australian National Electricity Market by an ensemble model of extreme learning machine. *IET Generation, Transmission & Distribution*, *7*(4), 391–397. https://doi.org/10.1049/iet-gtd.2012.0541

Zhang, S., Chen, R., Cao, J., & Tan, J. (2023). A CNN and LSTM-based multi-task learning architecture for short and medium-term electricity load forecasting. *Electric Power Systems Research*, *222*, 109507. https://doi.org/10.1016/j.epsr.2023.109507

Zhao, Z., Xia, C., Chi, L., Chang, X., Li, W., Yang, T., & Zomaya, A. Y. (2021). Short-Term Load Forecasting Based on the Transformer Model. *Information*, *12*(12), 516. https://doi.org/10.3390/info12120516