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Deep Learning-based Forecasting and Bidding Strategies: Analysis of Nepal's Participation in Indian Energy Exchange

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Abstract
Nepal in recent years has been participating in the energy trading on the Indian Energy Exchange (IEX) where it can import and export energy as required by participating in the bidding process. Initially started with the Day Ahead Market (DAM) trading only, Nepal has now also expanded into the Real-Time Market (RTM) since October 2023. However, inaccurate forecasts and Run-off-River Hydro-dominant power system have resulted in significant deviation charges for Nepal as power import/export deviates from scheduled power depending on grid conditions, highlighting the urgent need for improved forecasting accuracy. This underscores the critical importance of precise load forecasting to optimize bidding strategies and reduce deviation charges. To address this challenge, the paper proposes implementing a Deep Neural Network (DNN) model for DAM bidding and a Long Short Term Memory (LSTM) model for RTM bidding. It is shown through analysis that an accurate forecasting through advanced models like the DNN and LSTM is crucial for Nepal to minimize deviation charges, maintain grid stability, and reduce operational costs, highlighting the importance of effective implementation in both RTM and DAM. The DNN model significantly improves forecasting accuracy for generation (91%), load (89%), Market Clearing Price (MCP) (88%), and Tanakpur import/export (80%). Accurate load, generation, and bid forecasting in DAM could minimize deviation charges, while for unforeseen events, RTM takes care of the deviation, offering an additional layer of security and optimization. This paper recommends using LSTM model for adeptly adjusting schedules to real-time requirements, significantly improving the accuracy of Tanakpur bid (98.62%), DM bid (98.9%), and RT MCP (92.06%).

Keywords
Deviation charges, Deep Neural Network, Forecasting, Real Time Market, Long Short Term Memory, Indian Energy Exchange

1. Introduction

Nations worldwide are undergoing a transition towards renewable energy sources as part of efforts to mitigate carbon emissions, with a concurrent reduction in dependency on fossil fuel-based technologies [1]. Hydropower, acknowledged as a key renewable energy source, is valued for its affordability, minimal pollution emissions, and capacity to rapidly meet peak electricity demands [2]. Its substantial development in several countries has captured global attention. Nepal, heavily reliant on hydropower, faces challenges as it embraces renewable energy, which, although clean and cost-effective, introduces uncertainty into the electricity markets. The prevalence of Run-off-River and daily storage hydropower plants in Nepal often results in capacity shortages during the peak demand of the dry season, while surplus energy during the wet season necessitates exporting. Since 2016, Nepal has successfully navigated through a severe energy crisis, eliminating load shedding. This achievement is attributed to increased domestic power generation, transmission infrastructures and imports from India [3].

1.1 Energy Trading between Nepal and India

Nepal has interconnection with India through Muzzafurpur (400 kV), Kataiya (132 kV), Tanakpur (132 kV), Raxaul (132 kV), Ramnagar (132 kV),Sampatiya (132 kV), Jaleshwor (33 kV), Nanpara (33 kV), Raxaul (33 kV), Jaynagar (33 kV)and Kataiya (33 kV). Nepal imported electricity from the Indian Energy Exchange (IEX) via the Dhalke-Muzzaffarpur (DM) line on May 1st, 2021, and through the Tanakpur-Mahendranagar (TM) line on January 15th, 2022. Conversely, Nepal exported power to IEX through the DM line on November 3rd, 2021, and from the TM line in September 2023. Nepal began participating in RTM trading in October 2023. The approval to export power on IEX marks a significant milestone for Nepal in its power export initiatives. This achievement not only reduces the country's trade deficit with India but also helps manage seasonal energy surpluses until domestic demand rises significantly [3]. Nepal gained experience in competitive bidding for power exports involving Indian counterparts for the first time. Despite surplus energy during the wet season, Nepal still relies on India for power during dry months.During the FY 2022/23 NEA has imported the energy of 1,833 GWh during the dry season. The total consumption inside Nepal has increased from 8,870 GWh in previous year to 9,358 GWh, whereas the total export has been increased by approximately from 493 GWh in previous year to 1,346 GWh in FY 2022/23 [4].

1.2 Load Forecasting and Real-Time Market Dynamics

Ensuring balance between demand and supply in real-time operations is crucial for grid safety [5]. However, pre-trading in energy markets can lead to imbalances. To address this, policymakers introduced RTM, offering flexibility [6]. Nepal's involvement in the IEX market highlights its regional integration, though it faces deviation charges for any deviation from agreed upon energy transactions. Accurate load forecasting is necessary to efficiently plan and manage resources, minimize costs, maintain grid stability, facilitate market operations, and comply with regulatory requirements [7]. With the introduction of deviation settlement charges for unscheduled interchange, market participants in the IEX must forecast their loads in 15-minute time blocks a day in advance with high accuracy. System dispatchers must anticipate system load patterns to ensure sufficient generation capacity. Errors in load forecasts could lead to inadequate planning of reserve requirements, resulting in interruptions of load or deviation penalties. Adhering to schedules becomes crucial to avoid financial losses due to penalties [7].

Both accurate load forecasting and engagement in RTM trading are vital. They help manage fluctuations in variable renewable energy sources, influenced by factors like improper load forecasting, changes in weather, and unforeseen events. Accurate load forecasting ensures grid stability by anticipating demand, while RTM trading provides flexibility to adapt to sudden changes in supply and demand [2]. These measures are essential for maintaining stable and efficient electricity systems amidst evolving energy dynamics.There exists a multitude of methods for load forecasting, ranging from linear fitting and regression analysis models to various nonlinear models. Given that the actual electric load exhibits nonlinear behavior and is influenced by several factors such as temperature, humidity,wind, sunshine, rainfall, day of week,holidays and soon, traditional nonlinear forecasting models often fall short of meeting the accuracy demands of modern power systems [8].

Recently, researchers have investigated the application of deep neural networks to enhance the accuracy of load forecasting [9]. Different configurations of artificial neural networks have been utilized for this purpose, producing promising results. As the volume of data increases, the benefits of deep neural networks in this area become more evident. Their intrinsic ability to autonomously detect patterns and extract features from data containing multiple input variables makes them particularly suitable for tackling this challenge [10]. Long Short-Term Memory (LSTM) networks are a specialized type of Recurrent Neural Networks (RNNs) designed to effectively capture long-term dependencies within sequential data.

Unlike traditional RNNs, LSTMs excel at analyzing and modeling sequential data types, utilizing memory cells and gating mechanisms, LSTMs can selectively retain or discard information over time, allowing them to effectively learn patterns and trends in time series data [11]. This makes LSTMs particularly well-suited for tasks such as time series prediction, where accurate forecasting of future values based on historical data is crucial. In this study, we utilize a fully connected deep neural network to predict load, generation, and import values, essential for DAM bidding. Additionally, LSTM networks are employed to forecast import values based on two indices: DM and TM. These predictions are crucial for real-time bidding processes.

The RTM offers the opportunity to bid for power close to the actual delivery period, introducing flexibility and enabling efficient utilization of surplus generation capacity. By providing real-time balancing options, the RTM helps minimize operational deviations caused by forecast errors, thus enhancing the accuracy of real-time operations[5].

The major contributions of this paper are

- Develop precise forecasting models using DNN for DAM bidding, predicting load, generation, MCP, and import/export through DM and TM.
- Construct a bidding model for RTM utilizing Recurrent Neural Network (RNN)-LSTM, forecasting import/export through DM and TM, and RTM MCP, with RTM addressing unforeseen events.
- Investigate Nepal's engagement in both RTM and DAM on the IEX.
- Assess the improvement in accuracy following participation in both RTM and DAM, compared to DAM alone, to determine RTM's effectiveness in reducing forecast errors and managing DSM charges.

The paper is organized into five sections. Section 2 briefly presents the methodology used. Section 3 explains the experimental setup. Section 4 lists the results obtained and discusses them. Section 5 draws the conclusion.

2. System Modeling

DNN have become widely utilized in data-driven modeling, characterized by layers consisting of nodes and edges encoding mathematical relationships. During training, these relationships are updated iteratively through backpropagation.

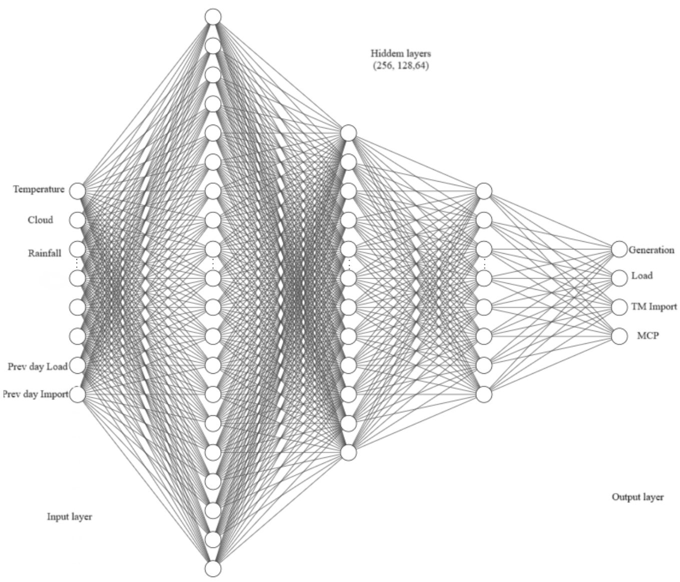

Figure 1: DNN Model architecture

In this paper, we employed a fully connected DNN-based model illustrated in Figure 1 due to its effectiveness in regression analysis. These networks excel at predicting variables like load, generation, and import based on historical and weather-related data. By capturing complex relationships between input variables and output predictions, these networks are well-suited for tasks influenced by multiple factors. Through training on historical data, including past load, generation, and import values, as well as weather-related features, fully connected neural networks can effectively anticipate future values. Their ability to automatically extract relevant features from the input data streamlines the prediction process. Thus, fully connected neural networks provide a powerful framework for DAM bidding, enabling accurate predictions of load, generation, and import values based on historical and weather-based data.

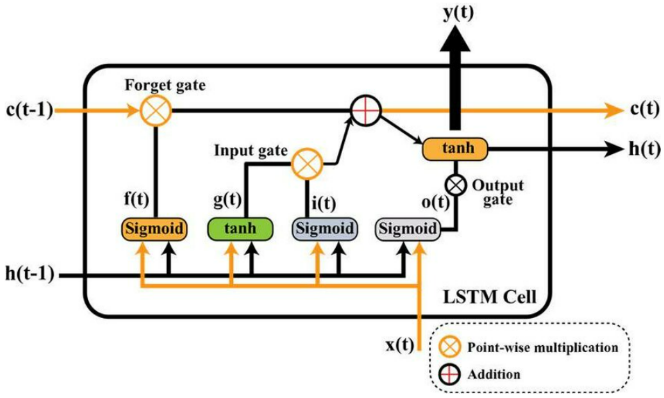

Figure 2: LSTM Model

LSTM networks are a type of RNNs specifically designed to capture long-range dependencies within sequential data [11]. Unlike standard RNNs, which commonly encounter issues with the vanishing or exploding gradient problem, LSTMs possess mechanisms that enable them to effectively process and retain information over prolonged time intervals [12]. In this paper, it is used for RTM bid as it comprises memory cells and gating mechanisms, which empower it to selectively remember or forget information depending on its significance to the current task. Training on historical data related to import/export and RTM MCP, LSTM networks are utilized for bidding purposes. This training process enables the LSTM model to identify intricate relationships among past import/export values, MCP, and other relevant variables specific to the energy market. Through the analysis of historical data, LSTM networks can detect recurring patterns and dependencies, enabling them to make precise predictions for future import/export values and MCP in the RTM. This capability is crucial in energy markets, where accurate forecasts are essential for optimizing bidding strategies and reducing costs.

3. Experimental Setup

Data spanning from March 2021 to January 2024 was collected from various sources including Load Dispatch Center log sheet, weather data from Open-Meteo, SCADA system for line loading, and information on holidays and Market Clearing Price (MCP) from open sources. To prepare the dataset for regression analysis, a careful selection of features and target variables was made based on the correlation shown in Figure 3. Historical data on imports, generation, and load were also incorporated as features to capture potential correlations with the target variables.

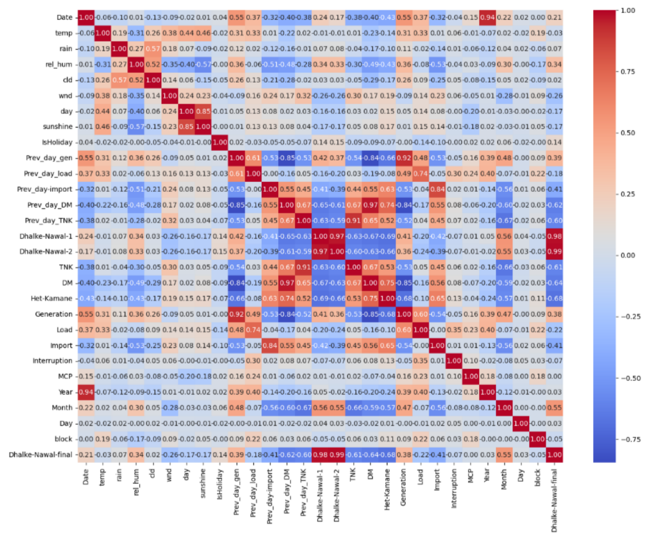

Figure 3: Correlation between target and features

The dataset was partitioned into training and testing subsets using an 80-20 split. For regression tasks, a fully connected DNN model was initialized using PyTorch with 17 input features and 4 target variables. The neural network was configured to undergo training for 150 epochs. During training, data was processed in batches, with 16 samples per batch utilized for training and 96 samples per batch used for testing. The learning rate was set to 0.0055. This value was determined through experimentation to achieve optimal convergence and performance of the model. Additionally, momentum, another hyper parameter involved in optimization algorithms, was specified as 0.5. Furthermore, a keep probability of 1 was set for dropout regularization, indicating that all neurons were retained during training.

Table 1: DNN Model Table

Hyperparameter	Description
Split ratio (training/testing)	80-20
Number of epochs	150
Batch size (training)	16
Batch size (testing)	96
Learning rate	0.0055
Momentum	0.5
Keep probability (dropout)	1
Random seed	42
Hidden Layer Size	3; 256, 128, 64 nodes
Loss function	Huber Loss
Optimizer	Adam

The neural network architecture comprised three hidden layers with 256, 128, and 64 neurons, respectively. These hidden layers, along with the input and output layers, collectively form the structure of the neural network, allowing it to learn complex patterns and relationships within the input data. For the optimization process during training, the Huber Loss function was chosen as the loss function. To optimize the model parameters, the Adam optimizer was employed. Overall, this configuration of hyperparameters as evident in Table 1, architecture, loss function, and optimizer settings was carefully chosen to train the neural network effectively and achieve accurate predictions for load, generation, line loading, and imports. We sourced actual and scheduled import data from DM and TM, along with pertinent parameters like deviation, deviation charges, and frequency, from the websites of the Eastern Region Power Committee and the National Load Dispatch Center, India (NLDC). These datasets are in a 15-minute time format, which is crucial for accurate forecasting as it adheres to the requirements of the bidding format.

In addition to employing a DNN model, we utilized LSTM networks to predict future values within the time series. LSTMs are well-suited for this task due to their ability to effectively capture relationships between past and future values. Leveraging actual import data from DM and TM, the LSTM model forecasted the import values required for bidding in the RTM. This approach ensured that our bidding strategy closely aligned with real-time market dynamics, thereby bolstering our capacity to make timely and well-informed decisions.

Following data preprocessing and normalization using the Pandas library, the dataset was divided into training and testing sets, with the training set comprising 75% of the total data and the testing set containing the remaining 25%. Each sequence in the dataset consisted of 16 time steps, representing the lookback window, allowing the model to consider the previous 16 time steps of data when making predictions for the next time step. Additionally, the model was trained to predict the values of the next 6 time steps, of which 2 time steps were used, providing a short-term forecasting horizon. The LSTM model featured an LSTM layer with 64 hidden units and 2 layers, followed by a fully connected layer. Training was conducted over 3 epochs using Mean Squared Error (MSE) loss and optimization with the Adam optimizer, as indicated in the Table 2.

Table 2: LSTM Model Table

Hyperparameter	Description
Split ratio (training/testing)	75-25
Sequence Length	16 time steps
Lookback Window	Previous 16 steps
input size	4
hidden size	64
num layers	2
Prediction	Predicts 6 steps, uses 2
Training Epochs	3 epochs
Loss Function	MSE
Optimizer	Adam
Test Loss	0.0002

4. Result and Discussion

Table 3: DNN Model Accuracy

Parameter	Accuracy
Model Accuracy (Generation)	91%
Model Accuracy (Load)	89%
Model Accuracy (MCP)	88%
Model Accuracy (TNK Import)	80%

During the testing phase, the DNN model exhibited notable accuracy in forecasting parameters crucial for day-ahead bidding in the power market. Specifically, the model achieved a high accuracy rate of 91% in predicting generation levels, essential for planning and scheduling power generation resources. Similarly, load prediction accuracy stood at 89%, providing reliable insights into electricity demand patterns. Furthermore, the model demonstrated strong performance in estimating MCP, with an accuracy of 88%. Additionally, it exhibited a reliable accuracy of 80% in forecasting TM bid, essential in bidding in DAM, as evident in Table 3.

Table 4: LSTM Model Accuracy

Parameter	Accuracy
Model Accuracy (DM)	98.9%
Model Accuracy (TNK)	98.62%
Model Accuracy (RT MCP)	92.06%
Application	Real-time market bidding

Figure 4 shows the generation predicted by DNN as compared with the actual values. Likewise Figure 5 shows the load predicted and Figure 9 shows the MCP predicted by the DNN model compared with the actual values. Also, figure 8 shows the TM import/export value predicted by the DNN model.The predicted import from TM is high during the hours when demand increases and during off peak hour it decreases. Likewise from the predicted value of load,generation, TM import ,DM import is predicted, the value when compared with actual value for blocks is as shown in Figure 7.

After analyzing the Figures, it becomes evident that our model performs effectively in predicting various parameters such as generation, load, MCP, and TM import. The predicted values closely align with the actual values, indicating the accuracy and reliability of our model. This close proximity between predicted and actual values demonstrates the effectiveness of our approach in forecasting electrical system parameters. Additionally, by utilizing the predicted values for DAM-DM bids, we can effectively optimize bidding strategies while adhering to the specified limits of 400 MW for DM bids and 70 MW for TM bids. The demonstrated accuracy and effectiveness of our model in predicting key parameters, along with its ability to accommodate bidding constraints, underscore its potential to support decision-making processes and optimize resource allocation in the power system.

After training, we assessed the model's performance on the test dataset, yielding a test loss of approximately 0.0002. LSTM model accuracy for DM was 98.9%, for Tanakpur import was 98.62% and for RTM MCP was 92.06%. Denormalizing both the predictions and actual values allowed for a direct comparison, revealing insights into the LSTM model's accuracy in forecasting import values for bidding in the real-time market. After training, our model was evaluated on the test dataset, yielding a test loss of approximately 0.0002.The close alignment between predicted and actual values as evident in Figure 7 to Figure 10, underscores the accuracy and reliability of our model. This close correspondence demonstrates the effectiveness of our approach in forecasting RTM bid parameters. Specifically, the model's capability to predict values accurately in real-time bidding scenarios indicates its potential to mitigate deviations that cannot be addressed by the DAM. By providing precise forecasts, our model enables better decision-making in RTM bidding, ultimately contributing to the management of deviations and the overall efficiency of the energy market.

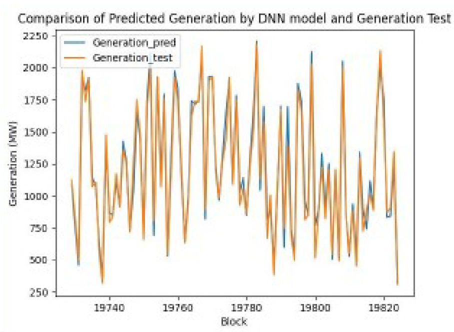

Figure 4: Generation Predicted by DNN value vs Test

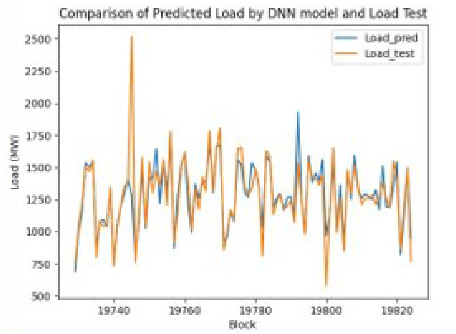

Figure 5: Load Predicted by DNN value vs Test

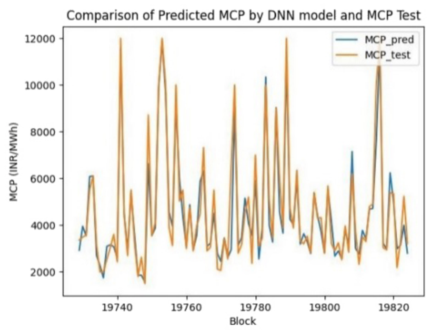

Figure 6: MCP predicted by DNN Model vs Test

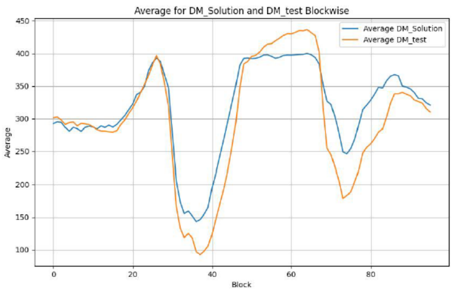

Figure 7: DM Import predicted by DNN model blockwise

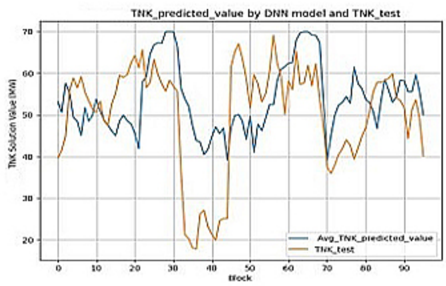

Figure 8: Tanakpur predicted by DNN model blockwise

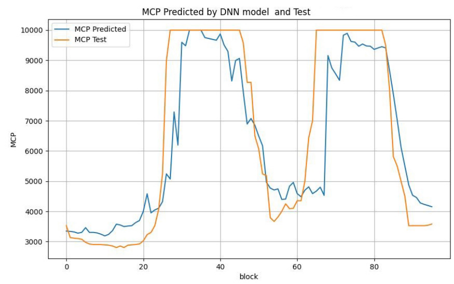

Figure 9: MCP predicted by DNN Model as per blocks

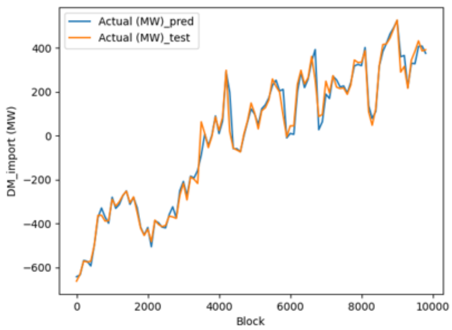

Figure 10: Actual Vs predicted DM Import by LSTM Model

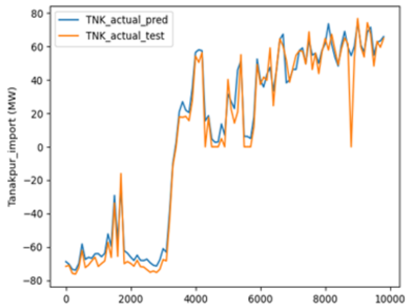

Figure 11: TNK Actual MW Import Predicted by LSTM

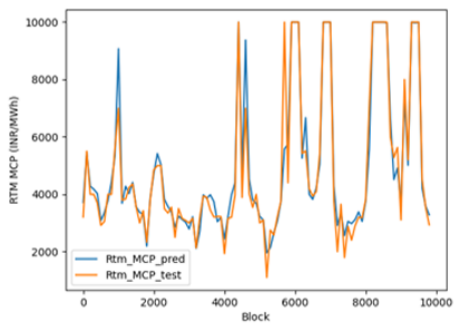

Figure 12: Real time MCP Predicted by LSTM

Given that RTM bidding occurs 1 hour prior to delivery time, with a 30-minute delivery window, our LSTM model is well-suited for RTM bidding. It utilizes a lookback window of the previous 16 blocks of data to forecast 2 blocks of data, facilitating effective RTM bidding. Utilizing the RTM model enables bidding closer to real-time, effectively managing deviations and potentially reducing DSM charges. Additionally, as depicted in the Figure 8 , our model not only ensures bids within the bid limit and MCP limit but also effectively handles outliers, maintaining prediction stability.

Furthermore, it is important to note that Nepal engages in both import and export transactions in the energy market. Figure 10 to Figure 12 illustrates how our model effectively predicts RTM values for both import and export scenarios. This capability allows Nepal to efficiently manage its energy trading activities, maximizing revenue from exports while meeting demand through imports. Ultimately, this contributes to the stability and reliability of the energy market. Using the RTM model allows us to bid closer to real time and if accurately bidded in RTM for both buy/sale as well in addition to DAM, deviations can be managed and the DSM charge is likely reduced.

5. Conclusion

In this paper, a DNN based model was developed that helps in forecasting load, generation, MCP, and the power traded through IEX which aids in bidding for the Day Ahead Market. Additionally, an LSTM model was used to predict the import and RTM MCP which was used for RTM bidding. The mismatch between the actual and schedule for which we had to pay the deviation charges was found to be reduced when traded in the RTM. The study underscores the critical importance of precise forecasting for facilitating bids that closely align with actual conditions in the DAM. Additionally, it highlights the pivotal role of RTM trading in managing unforeseen circumstances and reducing discrepancies between scheduled and actual energy usage. By adopting a proactive approach, leveraging accurate forecasting measures facilitated by DNN for DAM and LSTM for RTM bidding, the study demonstrates the potential to minimize deviation charges and enhance overall market participation efficiency. This suggests substantial advantages for Nepal's integration into the RTM on the IEX alongside DAM, provided it is executed effectively.

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