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Participation of Nepal in Real Time Market in Indian Energy Exchange: Analysis of Optimal Bidding Strategies using Machine Learning

by

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CERTIFICATE OF APPROVAL

The undersigned certify that they have read and recommended to the Institute of Engineering for acceptance, a dissertation entitled "**Participation of Nepal in Real Time Market in Indian Energy Exchange: Analysis of Optimal Bidding Strategies using Machine Learning**", submitted by **Elina Parajuli** in partial fulfillment of the requirement for the award of the degree of **Master of Science in Power System Engineering**.

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ABSTRACT

Precise load prediction is vital for electric utilities, as it provides crucial information for scheduling power generation, managing energy distribution, and optimizing resources. Nepal Electricity Authority, is currently participating in Indian Energy Exchange's (IEX) Day Ahead Market (DAM) for the import/export of electricity which is itself a huge milestone for Nepal but is also required to forecast their loads in 15-minute intervals a day in advance with high accuracy to bid in the energy market. To discourage excessive power drawl or insufficient power injection, a frequency-based component called the deviation settlement charge (DSM) is incorporated into the bulk electricity pricing in the IEX market. Due to in accurate load forecasting, weather changes, holidays, Nepal has also been subjected to deviation charges to account for any deviations from the agreed-upon energy transactions.

RTM provide a mechanism for balancing the fluctuations in supply and demand by allowing market participants to adjust their electricity purchases or sales in response to changing conditions. It also provides more flexibility and responsiveness compared to day-ahead markets, which can help grid operators manage their systems more effectively. Therefore, RTM bidding in addition to Day Ahead Market bidding is of paramount importance to handle this deviation.

This research presents a load, generation and import forecasting through two points Dhalkebar-Muzzaffarpur and Mahendranagar-Tanakpur using a Deep Neural Network (DNN) model which serves as Day Ahead Market bidding model. A Long Short Term Memory (LSTM) model is proposed alongside a DNN model for time series prediction. This LSTM model is tailored for Real-Time Market (RTM) bidding, allowing bids for power close to the actual delivery period. Its aim is to reduce the DSM charges, mitigate operational deviations due to forecast errors, and improve the precision of real-time operations. Additionally, a guideline-based model is devised to compute the deviation charges payable or receivable for deviations from the schedule.

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DAM	Day Ahead Market
RTM	Real Time Market
IEX	Indian Electricity Exchange Ltd.
TAM	Term Ahead Market
kV	Kilovolt
kVA	Kilo Volt Ampere
kW	Kilo Watt
kVAR	Kilo Volt Ampere Reactive
GWh	Giga Watt hour
MW	Mega Watt
DSM	Deviation Settlement Mechanism
DSC	Deviation Settlement Charge
INPS	Integrated Nepal Power System
FY	Fiscal Year
EScerts	Energy Saving Certificate
ACP	Area Clearing Price
MCP	Market Clearing Price
DM	Dhalkebar Muzzafarpur
TM	Tanakpur Mahendranagar
NEA	Nepal Electricity Authority
CERC	Central Electricity Regulatory Commission
ERPC	Eastern Region Power Committee
NVVN	NTPC Vidhyut Vyapar Nigam Ltd
NLDC	National Load Dispatch Center
DNN	Deep Neural Network
LSTM	Long Short Term Memory
NCD	Normal charges of Deviation

CHAPTER ONE: INTRODUCTION

1.1 Background

In response to the global imperative of reducing carbon footprints, numerous countries worldwide are transitioning towards renewable energy sources. They are progressively raising the proportion of renewable energy technologies in their energy generation portfolio while reducing dependence on fossil fuel-based technologies [1]. Hydropower, being the renewable energy source is widely recognized as a valuable energy source due to its low cost, minimal pollution emissions, and ability to respond quickly to peak electricity demands. Its significant development in several countries has garnered global attention.

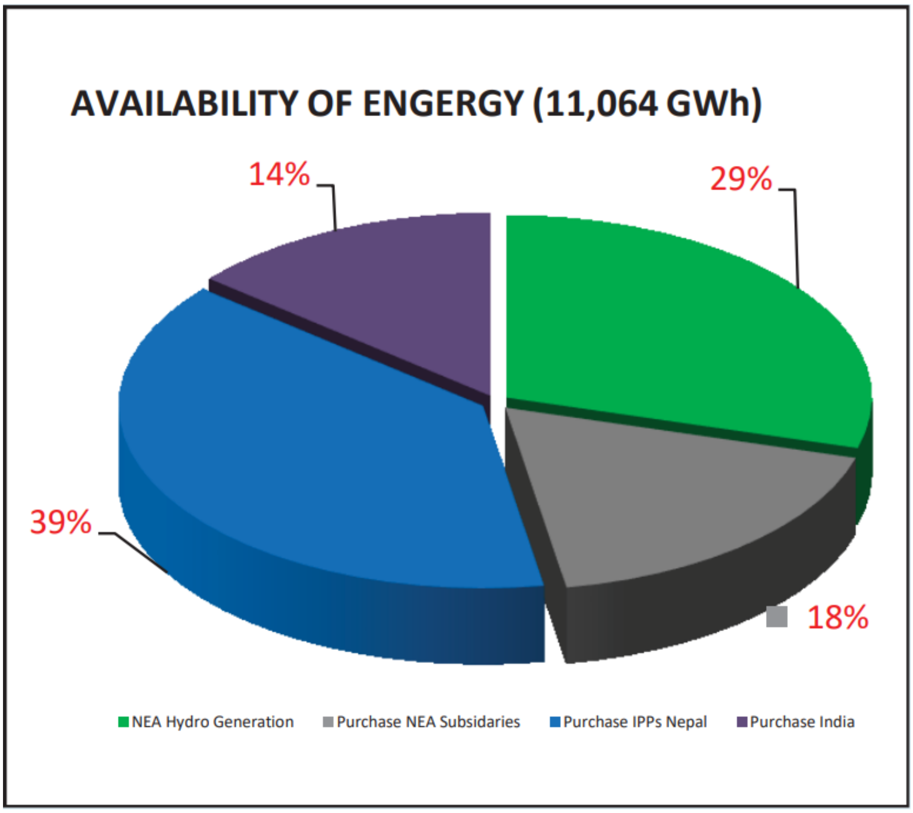

Figure 1.1: Availability of Energy in Nepal for FY 2021/2022 [2]

Nepal is among one of those countries that is highly dependent on hydropower for electricity. Although renewable energy is clean energy source with low production costs, it increases the uncertainty on the electrical markets due to their intermittent nature [3]. The prevalence of run-of-river and daily storage hydropower plants results in severe capacity shortages during the dry season when demand increases significantly. Conversely, during the wet season, there is an excess of energy in the system that needs to be exported [4]. Until 2016 AD, Nepal experienced a severe energy crisis. However, for the past seven years, Nepal has been free from load shedding [5]. This achievement is not only due to increased internal power generation but also because of power imports from India. This import of power takes place through points like Muzzafurpur (400 kV), Kataiya (132kV), Tanakpur (132kV), Raxaul (132kV), Ramnagar (132kV), Jaleshwor (33kV), Nanpara (33kV) and recently Sampatiya (132kV), at present.

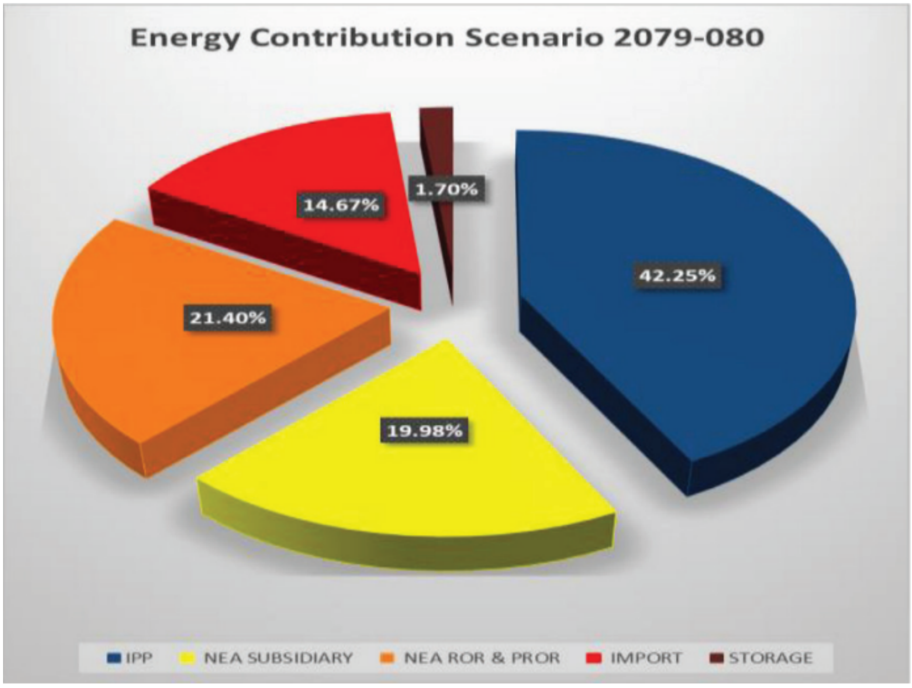

Figure 1.2: Energy Scenario in Nepal for FY 2022/2023 [4]

Since May 1st, 2021, Nepal has started importing power from the Indian Energy Exchange (IEX) through the Dhalke-Muzzaffapur 400kV line (DM), previously conducted bilaterally since February 17th, 2016. Additionally, as of January 15, 2022, Nepal has also begun importing power by bidding for the next day from the IEX through the 132 kV Tanakpur Mahendranagar (TM) transmission line, shifting from solely relying on bilateral transactions since 2008 through PTC India. Since November 3rd, 2021, following the Designated Authority's (DA) approval of the Devighat and Trishuli Hydroelectric Projects (HEP), Nepal has successfully sold a total of 39 MW of power through the DM line. This was achieved by submitting sell-bids for every quarter-hour interval of the following day's power export to the IEX. Subsequently, six additional projects with a combined capacity of 363.7 MW, followed by ten projects with a capacity of 452 MW, received approval for export to IEX. This milestone marks a significant achievement for Nepal in its power export efforts.

The process is continually expanding as more projects gain approval for power export to IEX, indicating substantial and ongoing progress in Nepal's energy sector. This progress helps alleviate the imbalance in trade with India while managing the seasonal excess energy until there is a substantial rise in domestic demand. NEA has acquired valuable expertise in competitive bidding for exporting power, initially engaging with Indian participants. Despite generating excess electricity during the wet season, Nepal continues to depend on imports from India to meet its power needs in the dry season. The power import in the fiscal year 2021/22 was 1,543 GWh from India, facilitated through both mutual agreements and IEX, while total power exports to India rose to 493 GWh, valued at NRs 15,466 million and NRs 3,884 million, respectively [2].

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]. This power trading experience demonstrated that NEA is making significant efforts to generate foreign currency through power exports to India. This trend is expected to expand in the future with the commissioning of more hydropower projects.

1.2 Types of Energy Markets in IEX

These are the types of energy market in IEX [6]:

1.2.1 Day Ahead Market (DAM)

The DAM facilitates the physical trading of electricity, enabling market participants to trade electricity, buying or selling for delivery at any or all 15-minute intervals within next 24 hours starting from midnight. Prices and quantities of the traded electricity are established through a bidding process involving two-way closed auction. Features of DAM are:

- Trading occurs in 15-minute intervals.
- An anonymous auction bidding process is employed on both sides.
- Approval from the State LDC (SLDC) is required by both buyers and sellers, subject to network availability and the presence of ABT meters.

- Congestion is managed by dividing the market into segments and setting specific Area Clearing Prices (ACPs) for each segment.

- Risk management includes mandatory margins, with potential additional margins specified for specific trading segments or contract types.

1.2.2 Intra Day, Day Ahead Contingency (DAC), Term Ahead Market

The Term-Ahead Market (TAM) offers various products enabling participants to engage in electricity trading on a term basis for periods extending up to 11 days in advance. TAM assists participants in effectively managing their electricity portfolios across different time durations. Features of TAM are:

- Trading of contracts specific to regions

- Guaranteed delivery

- The agreements within the TAM facilitate the assurance of electricity delivery several days ahead.

- Delivery Blocks: | Round The Clock (RTC) | Day | Night | Peak | Hourly |

1.2.3 Real Time Market (RTM)

The Real-Time Market (RTM) is a newly launched trading platform that started operating on June 1, 2020. This market conducts regular auction sessions every half an hour. Electricity traded during these sessions is slated for delivery either after four time blocks or one hour after the auction's gate closure. It determines the price and volume of electricity traded through a bilateral bidding process involving a closed auction. Features of RTM:

- Trading occurs in 15-minute contracts.

- Operates through a bilateral bidding process involving the closed auction.

- Participants must obtain clearance from the State Load Dispatch Center (SLDC) based on network availability and the presence of ABT meters.

- The Exchange publishes the Area Clearing Price (ACP) and Area Clearing Volume (ACV).

- Risk management within the Exchange involves utilizing bank balances and adhering to mandatory margin requirements, which may include additional margins specified for specific trading segments or contract types.

1.2.4 Green Day Ahead Market

The Green Day Ahead Market holds auctions for renewable energy a day before, utilizing a bilateral closed system to maintain anonymity. Currently, the Exchange invites bids from both conventional as well as renewable energy via separate bidding windows. The renewable segment, with must-run status, is cleared first based on transmission availability, followed by the conventional segment. IEX allows market participants to transfer unselected renewable bids at different prices.

Features of Green - DAM:

- Bid categories for Buyers and Sellers include solar, hydro, and non-solar.
- Distinct limits on quantities for sellers in solar, hydro, and non-solar categories.
- Participants can use 'Order Carry Forward (OCF)' to transfer uncleared bids to the conventional DAM at premium or discount prices.
- Trading of contracts in 15-minute intervals occurs through a bilateral anonymous closed bidding auction.
- Traders submit NOC from respective SLDC based on network availability.
- Managing congestion by dividing markets and establishing ACP.
- Separate price formation for green and conventional power.
- In order to control risk, required margin must be kept, which includes any extra margin called for by the specific trading sector or contract type.

1.2.5 Renewable Energy Certificates

The REC mechanism, established by the CERC, is designed to help state utilities and obligated entities acquire renewable energy, especially in areas with scarce renewable energy resources. It aims to set up a nationwide market enabling renewable energy generators to cover their costs. Each Renewable Energy Certificate (REC) represents the generation of 1 MWh of energy from renewable sources.Within the REC framework, generators have the flexibility to produce electricity from renewable resources anywhere in the country. They receive compensation equivalent to conventional sources for the electricity generated, while the environmental attributes are sold through exchanges at market-determined prices. Obligated entities nationwide have the opportunity to buy these RECs to fulfill their Renewable Purchase Obligation (RPO) compliance.

1.2.6 Energy Saving Certificates

As part of its initiative, Perform Achieve Trade also referred to as PAT is the scheme by the Ministry of Power that generates Energy Saving Certificates (ESCerts). These certificates serve as market-based instruments aimed at designated consumers (DCs) within energy-intensive industries and sectors. In each compliance period, these consumers receive targets to decrease their specific energy consumption.

1.2.7 Green Intraday-DAC-Term Ahead Market

G-TAM, recently introduced market category authorized by CERC for trading renewable energy. It offers Green-Day-ahead Contingency (DAC), Green-Intraday and Green-Weekly contracts. Matching mechanisms vary: Green-Intraday, Green-DAC, and Green-Daily use continuous/spot trading, while Green-Weekly employs a double-sided open auction.

Features of Green Intraday-DAC-TAM:

- A market mechanism designed to support national goals for increasing renewable energy capacity and integrating green energy throughout the nation.
- In G-Intraday and G-DAC, transactions are conducted within 15-minute intervals, whereas specific time blocks are traded in G-Daily and G-Weekly.
- All agreements within G-TAM are executed at the nation wide basis.
- Continual trading occurs in G-Intraday, G-DAC, and G-Daily, while G-Weekly employs a double-sided open auction bidding process.

1.3 Hydropower in Nepal and Nepal's Participation in IEX

Nepal heavily relies on hydropower as a primary source of electricity generation. The country's abundant rivers and mountainous terrain make it well-suited for hydropower development. However, the availability and generation of hydropower vary significantly with the seasons. During the wet season, which corresponds to the monsoon period from June to September, Nepal experiences heavy rainfall, leading to a substantial increase in water flow in rivers and streams. This abundance of water resources allows hydropower plants to operate at higher capacities, resulting in increased power generation. The wet season contributes to a significant portion of Nepal's hydropower production. On the other hand, during the dry season from October/November to May/June, precipitation decreases, resulting in reduced water flow in rivers. This limited water availability poses challenges for hydropower generation, leading to a decrease in power output. Nepal faces a lower hydropower generation during the dry season, and the country often needs to rely on alternative sources of electricity generation and imports to meet the demand.

Hydropower dominates Nepal's electricity generation landscape, constituting the majority [2]. This underscores the nation's heavy dependence on hydropower as its primary energy source. To mitigate seasonal variations and maintain a consistent electricity supply year-round, Nepal is pursuing diverse strategies. These encompass the expansion of hydropower capacity, the promotion of renewable energy alternatives such as solar and wind power, the adoption of energy storage solutions, and the improvement of grid infrastructure. These initiatives aim to effectively manage fluctuations in hydropower generation and cater to the escalating electricity needs of the country. Nepal has implemented a strategy to address the seasonal variation in hydropower generation, primarily relying on its run-of-the-river (ROR) hydropower plants. During the wet season, when Nepal experiences abundant water resources and higher hydropower generation, the country has leveraged this surplus power by exporting electricity to India. India, with its significant reliance on coal and solar power, often faces increased electricity demand during the wet season. Nepal's hydropower exports to India during this period help meet India's power requirements, reducing the need for additional coal-based power generation. This collaboration benefits both countries, as Nepal monetizes its excess hydropower capacity while supporting India in meeting its electricity needs with cleaner energy. Conversely, during Nepal's dry season when hydropower generation decreases, the country imports electricity from India. India's diverse energy mix, including thermal and solar power, allows it to meet Nepal's power demands during this period when Nepal's own hydropower production is relatively lower. This import arrangement helps bridge the electricity gap in Nepal and ensures a stable supply for domestic consumption.

Currently Nepal has been participating in energy trading in an IEX. Electricity trading between South Asian nations through long-term bilateral contracts was already established prior to the introduction of the Cross-Border Electricity Trade (CBET) Regulations by the Central Electricity Regulatory Commission (CERC) in 2019. These regulations aim to enhance efficiency and transparency by enabling electricity trade through energy exchange platforms. Facilitating inter-country power trade through the Exchange Market under these regulations can lead to competitive price discovery and optimal power procurement. Since May 2021, Nepal has been actively participating in India's Day-Ahead Market to address its dry season electricity demand. Since November 2021, NEA has been selling excess electricity generated during the monsoon season in the DAM operated by IEX, resulting in significant revenue generation for the country. By August of that year, electricity trade with India had generated INR 4.50 billion for Nepal, with INR 1.51 billion earned in August alone. Between May and August, over 780 million units of electricity were sold in the Indian market, generating about INR 7.2 billion [7].

Nepal participates in the DAM through the IEX, supported by its trading partner NVVN (NTPC Vidhyut Vyapar Nigam Ltd.). Trading occurs for all or any fifteen minute time intervals within the following 24-hour period, starting from midnight. Prices and volumes are established using a two-sided closed auction bidding system. Managing imbalances between scheduled and actual energy transactions is vital due to the unpredictability of power generation and consumption. Ensuring system reliability and stability demands strict grid discipline, with all entities adhering to scheduled power drawl/injection. Significant deviations can cause major grid frequency fluctuations, risking power system security [8]. Since October 2023, Nepal's participation in IEX's RTM marks a significant step in managing real-time deviations that the DAM alone couldn't address.

1.4 Problem Statement

Participation in the DAM on the IEX can indeed be considered a significant achievement for Nepal. It demonstrates Nepal's integration into regional electricity markets and its ability to engage in cross-border electricity trading. However, it is important to note that, like any participant in such markets, Nepal has been subjected to deviation charges to account for any deviations from the agreed-upon energy transactions. To discourage excessive power drawl or insufficient power injection, a frequency-based component called the deviation settlement Mechanism (DSM) charge is incorporated into the bulk electricity pricing. Utilities are required to pay/receive the DSM charge for any power drawls exceeding the scheduled amount or injections falling below the scheduled amount to compensate for the cost of balancing the grid and maintaining stability. This charge is intended to encourage participants to accurately schedule and trade energy. Due to the significant fluctuations in hydro generation, which are dependent on weather conditions, and the wide variation in load, along with the absence of accurate load forecasting, Nepal has incurred substantial costs from DSM charges.

Hence, an accurate methodology is imperative for load forecasting. Additionally, the implementation of RTM is crucial for maintaining the balance between electricity supply and demand in the moment. Unlike DAM, which facilitate electricity transactions for the following day, RTM allow trading through auction session starting every thirty minutes. Power delivery is scheduled for 1 hour after the auction gate closes (spanning four time blocks). This feature is particularly vital for managing electricity systems reliant on variable renewable energy sources like hydro, wind, and solar power. These sources can exhibit unpredictability and sudden output fluctuations due to weather variations.

RTM offer a solution by enabling market participants to adapt their electricity transactions promptly in response to evolving conditions [9]. RTM offer heightened flexibility and responsiveness in contrast to DAM, enhancing the efficacy of grid management for operators. In instances of abrupt spikes in electricity demand prompted by extreme weather or unforeseen circumstances, RTMs play a pivotal role in ensuring ample supply to meet the surge in demand. Ultimately, RTM serves as a cornerstone of contemporary electricity systems, providing the necessary framework to dynamically balance supply and demand in real-time, which is critical for maintaining grid stability and reliability.

An accurate methodology needs to be developed for day-ahead load forecasting and generation planning, as well as predicting the Market Clearing Price (MCP). This methodology should consider factors such as temperature, cloud cover, humidity, holidays, discharges, previous day's load, and line loading to ensure precise prediction of bids for the DAM. Additionally, Nepal's participation in the RTM of the IEX should be explored to evaluate its effectiveness in minimizing the substantial DSM charges Nepal has been paying. To quickly adapt to sudden changes in supply

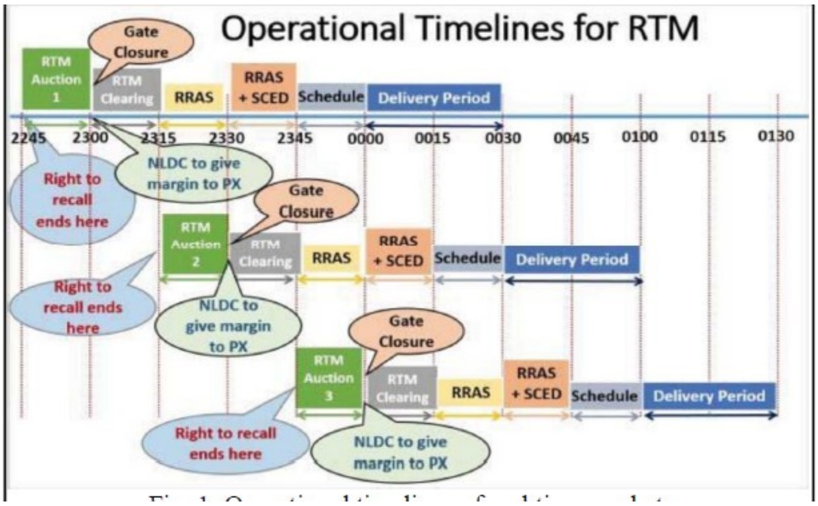

Figure 1.3: Timeline of RTM [6]

and demand dynamics, RTM in addition to DAM are essential. By providing RTM option, these approaches help minimize operational deviations caused by forecast errors, thus enhancing the accuracy of real-time operations. Furthermore, an accurate method for predicting the value of bids required in the RTM should also be developed. The scope and objectives of this thesis are based on these requirements.

1.5 Scope of this thesis

This thesis aims to analyze the dynamics between real-time and day-ahead competition within the Integrated Nepalese Power System (INPS). The scope extends to the development of a fully connected Deep Neural network to predict load, generation and import in the Day Ahead Market, utilizing variables such as cloud cover, wind speed, rainfall, day of the week, sunshine duration, temperature, relative humidity, holidays, discharge and historical load data. Furthermore, another aspect of the scope involves creating a Long Short-Term Memory (LSTM) model to forecast import/export requirements based on real-time data which will be used for RTM bidding. Additionally, the scope includes developing a model aligned with CERC guidelines to calculate DSM charges based on factors like actual, scheduled, frequency, and normal deviations. Lastly, the scope encompasses analyzing the potential implications of Nepal's participation in the Real-Time Market on the IEX to minimize DSM charges within the INPS.

1.6 Objectives

The primary objective of this study is to develop analytical tools aimed at understanding potential marketing models for adoption by INPS in order to minimize the DSM charge. The specific objectives of the thesis are derived from the primary objective and are enlisted here.

- Develop a forecasting model for DA load, generation, MCP, and Import by taking into account several variables including:
  - Weather: temperature, rainfall, relative humidity, cloud cover, wind, discharge of some rivers, sunshine
  - Day of the week, Holidays
  - Historical load, generation, and line loading profile
- Formulate a method to prepare and process the dataset coming from multiple sources to train and deploy the forecast model.
- Devise heuristic to determine DAM Bid.
- Develop a time series prediction model that uses LSTM to predict the import/export required, based on RT values so far available to us and generate RTM bid.
- To develop a model based on CERC guidelines that calculates the DSM charge that has to be paid /received based when provided with actual, schedule, frequency and normal charges of deviation for the block.
- Analysis of Nepal's participation in IEX RTM in addition to DAM with respect to import cost and interruption and to minimise DSM charge.

1.7 Thesis Organization

The dissertation is organized into seven chapters. This section enlists a brief outline of each chapter and its contents.

- This chapter describes the energy senario in Nepal and introduces the types of market in IEX. The problem statement is described and followed by specifying the scope and objectives of the thesis work.
- Chapter 2 provides the literature review on the types of energy market implemented worldwide.
- Chapter 3 includes the theoretical background on various concepts implemented in this thesis.
- Chapter 4 describes market model and DSM mechanism as per CERC guidelines for calculation of DSM charge in Nepal's case. Additionally, an optimization problem is formulated based on the assumptions and system model considered for this study.
- Chapter 5 outlines the research design and methodology, discussing the overall framework for achieving the thesis objectives.
- Chapter 6 discusses the system considered and tools used in the thesis work and presents the simulation approach and results.
- Chapter 7 concludes the findings of this study along with the future research directions of this thesis.

CHAPTER TWO: LITERATURE REVIEW

Numerous countries across the globe are undergoing a profound transformation of their energy systems [1]. Driven by the imperative to mitigate CO2 emissions, these nations are progressively amplifying the proportion of renewable energy (RE) technologies in their power generation portfolio while concurrently diminishing the reliance on fossil fuel-based technologies [10] - [11].

In an electricity system, maintaining a balance between demand and supply is crucial in real time operations [12]. However, due to the pre-trading of energy in forward, day-ahead, and intraday markets, imbalances can arise between the anticipated and actual supply and demand levels, leading to deviations from the desired equilibrium [13]. The system frequency serves as the pulse of an interconnected power system, constantly indicating the equilibrium between load and generation. Any deviations from the designated 50 Hz set point indicate either an excess or a shortfall of generation across the entire system. In response to the concerns regarding grid safety and security, policymakers have developed the RTM as a solution [14]. The RTM aims to provide contracts on a real-time basis, addressing the issue by allowing market participants to trade electricity and manage supply and demand in a more immediate and dynamic manner [15].

The majority of electricity produced in Nordic energy market is traded on it's DAM, known as Elspot. Producers, sellers, and significant industrial consumers can manage their electricity commitments on NP's intra-day market, known as Elbas. Elbas commences trading two hours after the conclusion of Elspot's trading session and concludes one hour before the commencement of electricity delivery. [9]. This enables market participants to oversee their electricity positions and make essential adjustments as the delivery time approaches [9]. In Italy's power market, there is a Day-Ahead (DA) market where the gate closure time (GCT) is scheduled for 12:00 PM on the day before delivery day. Following the deadline, three Intraday auctions are conducted to adjust the power schedules based on the DAM. Additionally, starting from September 21, 2021, Italy became a part of the continuous cross-border intraday (XBID) market. This integration enables trades to be made up until one hour prior to the delivery period, providing further flexibility and opportunities for market participants [16].

In India, the short-term electricity market operates through power exchanges, facilitating the trading of standardized contracts for intraday and day-ahead transactions. Historically, market participants would rely on frequency-based grid balancing mechanisms in the absence of real-time contracts. However, this practice raised concerns regarding grid safety and security. At present, India manages real-time energy imbalances through mechanisms such as the DSM and Ancillary Services (AS) Mechanism, bilateral contingency transactions within the day, the intra-day market segment facilitated by power exchanges, and the rescheduling or revision of schedules for upcoming time blocks (known as the Right to Recall). These processes are implemented to ensure effective management of real-time energy imbalances and to uphold grid stability in the country. [17]. To tackle this issue, policymakers introduced the RTM in 2020, offering contracts for real-time transactions. Within a short period of time, the RTM has gained substantial liquidity and has become the second most popular avenue in terms of the number of transactions conducted [15].

In May 2021, Nepal commenced trading in the DAM of the IEX as part of its participation in CBET, supported by NVVN, its trading partner. Since November 3, 2021, the NEA has begun exporting surplus energy from the wet season to India's DAM through the submission of sell bids for each 15-minute time slot the following day via power exports to the IEX. This was facilitated using the DM 400 kV transmission line. Additionally, starting January 15, 2022, NEA initiated power imports on a DA basis from IEX through the 132 kV TM transmission line, marking a shift from exclusive reliance on bilateral transactions. Even with an excess of electricity during the wet season, Nepal continues to depend on India for power in the dry months, largely because of the prevalence of run-of-the-river (RoR) projects. 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].

Participating in DAM is a huge milestone for Nepalese power system however due to variability of generation and demand depending on weather, public holidays, lack of accurate load forecasting methods, there has been some days in which huge deviation from schedules occur on the day of operation. These are settled through DSM [18]. The deviation charges are to be paid as per the regulation of CERC and Nepal has been paying a huge amount of deviation charge.

The implementation of RTM for trading has helped to balance the deviation that occurs in trading in various power market in the world [14]. The United States of America has developed a unified network of power markets overseen by Independent System Operators (ISOs) and Regional Transmission Organizations (RTOs) [19]. The RTOs and ISOs are regulated by the Federal Electricity Regulatory Commission (FERC). Within the USA, these ISOs/RTOs facilitate trading opportunities in DAM and RTM, while also addressing various requirements of the power system [20].Settlement in the DAM is computed hourly, whereas the RTM determines balancing settlements using actual five-minute revenue data, accounting for discrepancies in megawatt quantities from the scheduled DA quantities. Implementation of the RTM from June 1, 2020, has provided an opportunity to strengthen power markets in India [21].

Nepal commenced its participation in the IEX RTM in October 2023. Effective engagement in RTM can help mitigate discrepancies that may arise between the DAM and subsequent adjustments through DSM. The DAM allows participants to bid on power delivery for the following day, whereas RTM permits bids closer to real-time delivery, offering flexibility and real-time balancing options. This framework optimizes surplus generation capacity and reduces operational deviations caused by forecast errors, thereby enhancing real-time operational precision. Recently, researchers have explored the use of Deep Neural Networks (DNN) to improve the accuracy of load forecasting [22]. The innate ability of DNNs to identify patterns and extract features from complex datasets makes them particularly well-suited for this application [23]. Although there is a limited body of literature on forecasting and machine learning within electricity markets [23, 24, 15, 25], and only a few studies address bidding strategies [21, 12, 25], there is a notable gap in research focused on minimizing energy trading costs with an emphasis on DSM charges and bidding strategies, particularly in hydropower-centric systems like Nepal. This research aims to develop a data-centric decision-making model to minimize DSM charges through optimal bidding strategies for the DAM and RTM using deep learning-based regression and time-series prediction models. Existing literature covers effective DSM modeling for system stability, but there is a lack of research on large-scale forecasting for INPS and reducing DSM charges from the perspective of market participants like INPS in IEX. Optimal bidding strategies are well-documented for US, European, and Indian markets. INPS's dual role as both buyer and seller needs to be included in the model.

As a result, this thesis aims to develop a deep neural network, to forecast load, generation, and DAM bids. It seeks to utilize RTM specifically utilizing LSTM models, to address real-time fluctuations in load and generation profiles that DAM may not capture adequately. Additionally, the thesis aims to analyze Nepal's integration into the IEX RTM alongside DAM to reduce DSM charges caused by load and generation variability, as well as forecast errors, through effective Real Time Trading strategies.

CHAPTER THREE: THEORETICAL BACKGROUND

3.1 Machine Learning

Machine learning (ML) is branch of computer science and artificial intelligence (AI) that employs algorithms and data to mimic human learning processes in AI systems, enhancing their precision as they accumulate experience.

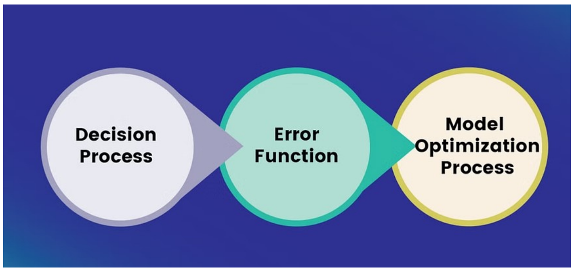

Figure 3.1: Working of Machine Learning [26]

Machine learning algorithms consist of three primary components:

a. Decision Process: These algorithms are usually used to categorise or predict data. The algorithm draws conclusions about patterns in the input data by examining the data, which can be either categorised or uncategorized.

b. Error Evaluation: The model's predictions are evaluated using an error function. This function assesses the correctness of the model by comparing predictions with actual outcomes when given examples that are known.

c. Model Optimization: It includes reducing the distinction between forecasted and observed values by tuning the model's parameters to more closely align with the data points in the training dataset. Until a sufficient degree of precision is attained, this self-paced, iterative process of assessment and modification continues.

3.1.1 Types of Machine Learning

i. **Supervised Machine Learning**

Supervised learning employs datasets with predefined labels to train algorithms efficiently. By supplying labeled input data, the model fine-tunes its parameters through an iterative process to achieve an accurate fit. This process often includes cross-validation methods to reduce the risks of overfitting

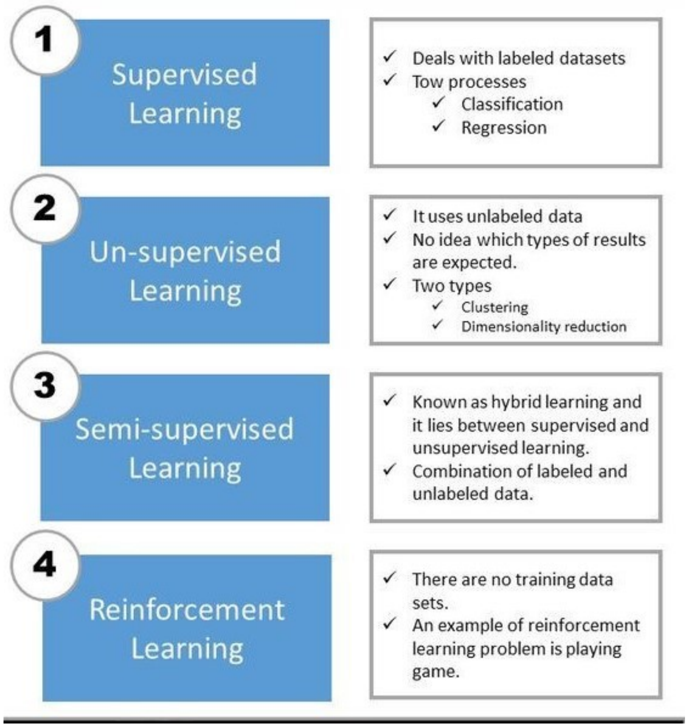

Figure 3.2: Types of Machine Learning [27]

or underfitting. Common techniques in supervised learning include linear regression, neural networks, logistic regression, naive Bayes, random forests, and support vector machines (SVM).

ii. **Unsupervised Machine Learning**

Unsupervised learning classifies and analyses unlabeled datasets into meaningful groups using machine learning methods. Without depending on predetermined labels, these algorithms find hidden patterns or groupings within the data. Unsupervised learning is useful for applications like client segmentation, exploratory data analysis, cross-selling tactics, picture and pattern recognition, because it can reveal underlying patterns. Principal component analysis (PCA) and singular value decomposition (SVD) are two further approaches used by these methodologies to assist minimise feature complexity. Neural networks, k-means clustering, and probabilistic clustering are common techniques in unsupervised learning.

iii. **Semi-Supervised Learning**

Semi-supervised learning strikes a balance between supervised and unsupervised learning approaches. It learns to classify and extract features from a larger unlabeled dataset using a smaller tagged sample. When labelling data is either too expensive or inadequate for supervised learning algorithms to employ, this approach performs admirably.

iv. **Reinforcement Learning**

Although reinforcement learning shares certain characteristics with supervised learning, it is distinct in that it does not require pre-existing sample data for training. Rather, it learns by making mistakes and then building on successful results to create the best possible tactics or policies for a particular issue.

3.2 Artificial Neural Network

Artificial Neural Networks (ANNs) are structured systems composed of artificial neurons called units. These units are arranged into layers within the network architecture, facilitating complex information processing similar to biological neural networks [28]. Depending on how difficult the network's learning objectives are, the number of units in each layerwhich normally consist of input, hidden, and output layerscan vary. External data is received for processing by the input layer which it needs to learn patterns or analyze after which it moves through the hidden layers and is transformed before arriving at the output layer, which produces a response. Units in different layers are connected to each other through connections that convey data and are weighted to determine the influence of one unit on another. The neural network gains patterns in the data by means of these weighted connections, progressively refining its comprehension until it generates an output. Artificial neural networks imitate this biological organisation by modelling their architecture and functions after those of human neurons.

3.2.1 Deep Neural Network

Deep neural networks (DNNs) represent a more sophisticated evolution of artificial neural networks (ANNs), capable of tackling complex tasks that traditional ANNs struggle with [30]. While ANNs typically consist an input layer with one or two hidden layers and finally an output layer, DNNs are characterized by having multiple hidden layers. These extra layers significantly enhance the network's ability to process intricate patterns and understand complex data relationships. The depth

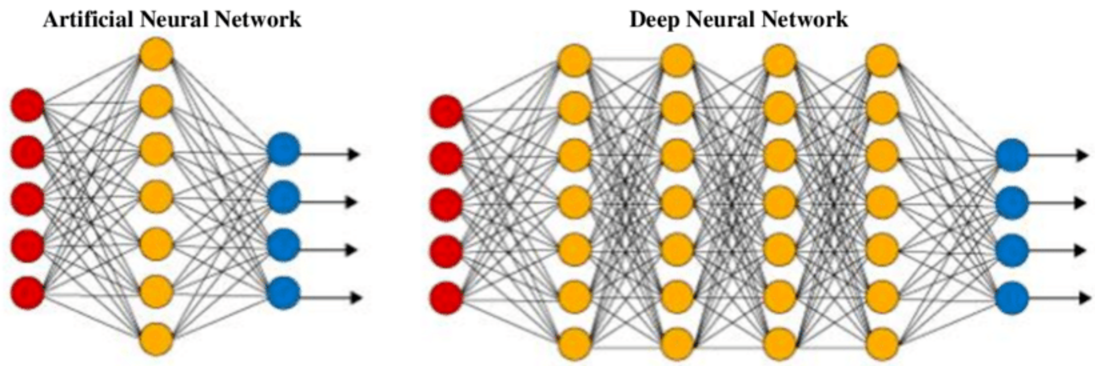

Figure 3.3: Artificial Neural Network vs. Deep Neural Network [29]

and complexity inherent in DNNs allow them to transform inputs into highly accurate and optimized outputs. This increased number of layers boosts the model's capacity to tackle complex problems, making DNNs essential for achieving superior performance in various deep learning applications. Consequently, DNNs have gained widespread popularity and success across numerous fields, demonstrating remarkable efficiency and effectiveness.

3.2.1.1 Activation Function

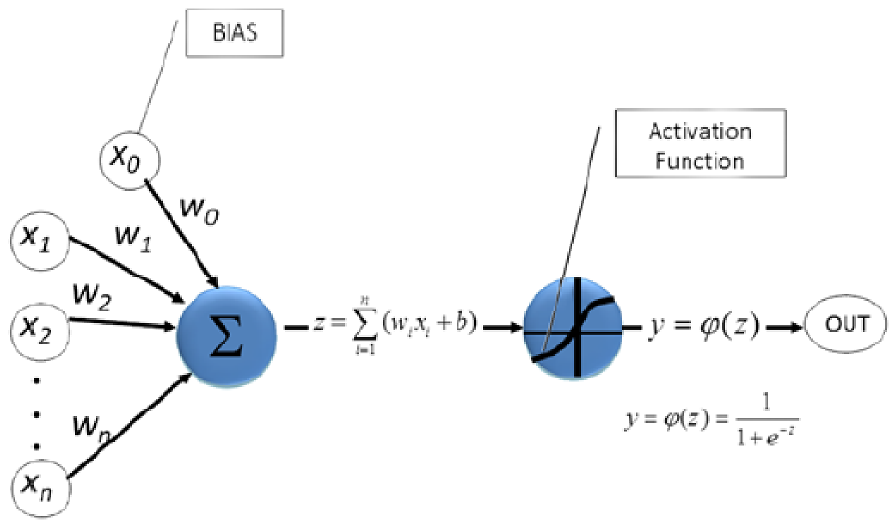

Figure 3.4: Activation Function [30]

An activation function is a fundamental element within neural networks that determines the output of each unit, such as a perceptron or neuron. It processes input from each neuron and transforms it into an output, typically within the range of 0 to 1 or -1 to 1. Essentially, it represents the additional influence applied to the input to precisely shape the output. The activation function decides whether a neuron should be activated, assessing the importance of the neuron's input to the network during the prediction process through straightforward mathematical operations. Activation functions are pivotal in neural networks as they process inputs to generate the desired outputs.

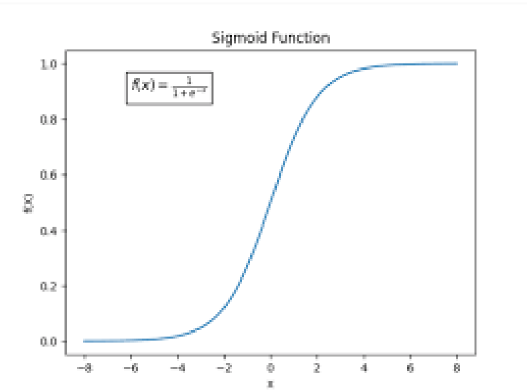

Figure 3.5: Sigmoid Activation

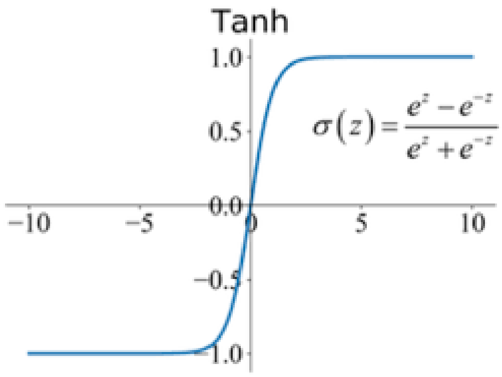

Figure 3.6: TanH Activation

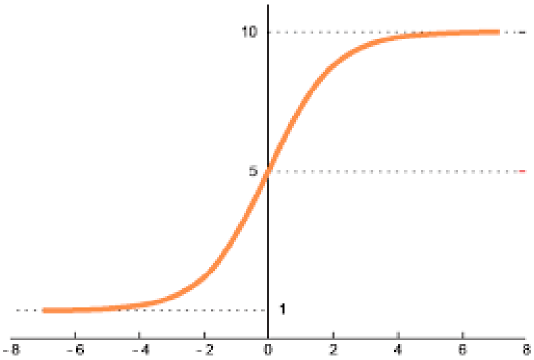

Figure 3.7: Softmax Activation

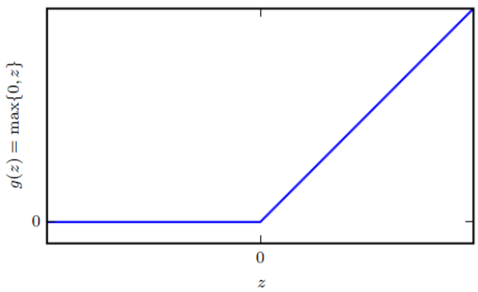

Figure 3.8: ReLU Activation

[31]

Real-valued inputs are sent into a neural network's neurons, each of which has a weight. After being multiplied by the weights, these inputs are sent to the activation function. The output of every neuron thereafter serves as the input for neurons in the layer above, and so on, recursively through a multitude of activation functions, until the output layer generates a prediction.

In order for neural networks to learn complex patterns, it's important to remember that they depend on nonlinear activation functions. The activation function's derivative also plays a crucial role in the backpropagation process, which makes it easier to learn and modify network settings. The following noteworthy activation functions are listed:

1. The sigmoid function produces output values ranging from zero to one with a smooth gradient. However, it encounters the vanishing gradient issue for extremely high or low input values, significantly hindering the network's predictive capabilities.

2. The zero-centered nature of the TanH function makes it useful in some cases when modelling strongly positive, strongly negative, or neutral inputs. It is computationally intensive because it uses an exponential function and encounters the vanishing gradient issue as well.

3. Softmax functions as a specialised output neuron activator. In the range of 0 to 1, it normalises the outputs for every class and produces probabilities that show how likely it is that the input belongs to a particular class. Nevertheless, there are difficulties in training the neural network while utilising the exponential function. An output value's exponential, for example, can produce extremely huge values. Because floating-point computer representations have constraints, using these huge numbers in future operations, such loss computation, may result in numerical instability.

4. Rectified Linear Units, or ReLUs for short, are the most popular activation functions in nearly all convolutional neural networks and deep learning models because of their excellent computing efficiency. The ReLU is half rectified (from bottom), as figure 3.8 illustrates. When z is less than zero, $f(z)$ is zero; conversely, when z is larger than or equal to zero, $f(z)$ is equal to z.

   The Rectified Linear Unit (ReLU) activation function possesses several key characteristics:

   - **Non-Linearity:** ReLU introduces non-linearity into the model, despite its simplicity, which enables neural networks to learn complex patterns.

   - **Sparsity:** ReLU can lead to sparse activations, outputting zero for any negative input. This sparsity can enhance the efficiency of the network.

   - **Computational Efficiency:** ReLU uses a straightforward thresholding process at zero, making it computationally efficient.

   - **Gradient Propagation:** ReLU assists in mitigating the vanishing gradient issue that may arise when using other activation functions, like the tanh or sigmoid. Gradient flow is maintained during backpropagation when the gradient is 1, which is the case for positive inputs.

3.2.1.2 Loss Function

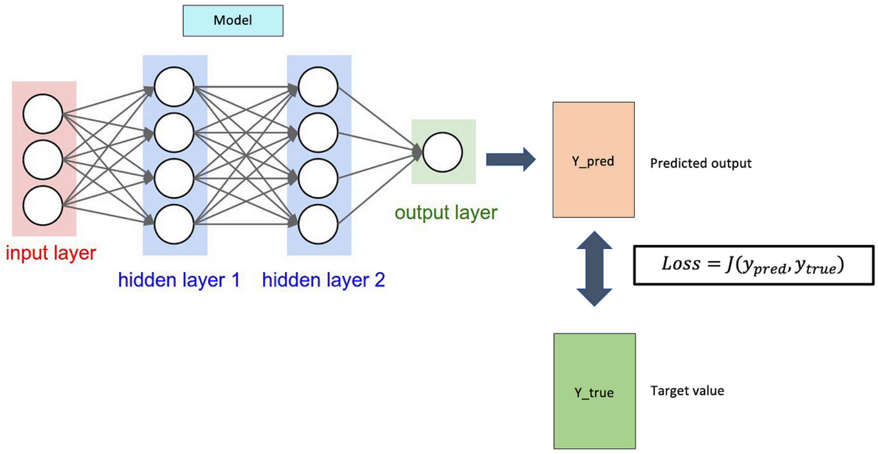

Figure 3.9: Loss function [32]

A loss functionalso referred to as a cost function or an objective functionis a crucial part of a DNN that calculates the discrepancy between the goal values in a dataset and the anticipated outputs produced by a neural network. Quantifying the model's performance on a particular task is the primary goal of a loss function. The difference or error between the predictions and the actual is assigned a numerical value. The ultimate objective of training is to minimise the loss function, which is accomplished by iteratively updating the parameters and improving the network's prediction accuracy.

The type of loss function used depends on the nature of the problem. Some of the types of loss function are:

i. **Mean Square Error (MSE) / L2 Loss**

Mean Square Error (MSE) or L2 loss is used to calculate how much of an error there is between the output of a machine learning system and its predictions. The average of the squared discrepancies between the goal values and the forecasted values is used to achieve this. MSE penalizes larger deviations from the target value more severely by squaring these differences. The total error is then normalized by averaging these squared errors relative to the number of samples or observations in the dataset.

The mathematical formula for Mean Square Error (MSE) or L2 Loss is:

$$\text{MSE} = \frac{1}{n} \sum (y_i - \hat{y})^2$$

In this context:

- n stands for the total sample numbers in the dataset
- y_i is the desired output value for the i-th sample
- $\hat{y}$ denotes the predicted value for the i-th sample

ii. **Mean Absolute Error (MAE) / L1 Loss**

Mean Absolute Error (MAE), also known as L1 Loss, is a loss function used in regression tasks. It calculates the average absolute differences between the predicted values and the actual target values. Unlike Mean Squared Error (MSE), MAE does not square the differences, giving equal weight to all errors regardless of their magnitude.

The mathematical formula for Mean Absolute Error (MAE) or L1 Loss is:

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

Where:

- n is the number of samples in the dataset
- y_i is the target value for the i-th sample
- $\hat{y}$ is the predicted value for the i-th sample

iii. **Huber Loss**

Huber Loss, also known as Smooth Mean Absolute Error, is a loss function that combines the beneficial characteristics of Mean Absolute Error (MAE) and Mean Squared Error (MSE) into one. This hybrid nature makes Huber Loss less sensitive to outliers, similar to MAE, while still penalizing minor errors, akin to MSE. It is commonly used in regression tasks in machine learning.

The mathematical equation for Huber Loss is:

$$L(\delta, y, f(x)) = \begin{cases} \frac{1}{2}(f(x) - y)^2 & \text{if } |f(x) - y| \leq \delta \\ \delta |f(x) - y| - \frac{1}{2}\delta^2 & \text{if } |f(x) - y| > \delta \end{cases}$$

Where:

- L is the Huber Loss function
- δ is the delta parameter, which determines the threshold for switching between the quadratic and linear components of the loss function
- y is the true value or target value
- $f(x)$ is the predicted value

iv. **Binary Cross-Entropy Loss / Log Loss**

Binary Cross-Entropy Loss quantifies the gap between predictions and the actual target values. It is calculated as the negative sum of the logarithms of the predicted probabilities and is extensively used in logistic regression and in training artificial neural networks to determine the likelihood of a data sample belonging to a specific class, internally utilizing the sigmoid activation function.

To better understand Binary Cross-Entropy Loss, it is helpful to break down its components:

- **Loss:** This is a mathematical measure of the difference between the algorithm's prediction and the actual target value.
- **Entropy:** In simple terms, entropy measures the degree of randomness or disorder within a system.

- **Cross-Entropy:** Commonly used in information theory, cross-entropy measures the differences between two probability distributions and can be used to assess an observation.

- **Binary:** This refers to a system of numerical representation using two states, 0 and 1. In the context of binary classification, two classes (A and B) are distinguished using binary representation, with class A assigned 0 and class B assigned 1.

Loss Function	**Application**
Mean Absolute Error (MAE)	When the goal is to have a stable and interpretable model, and outliers should not be heavily penalized.
Mean Squared Error (MSE)	When it is important to give higher weight to larger errors, or when the data distribution is Gaussian.
Huber Loss	When a balance between MAE and MSE is desired, or when dealing with datasets containing outliers.
Binary Cross-Entropy Loss	In binary classification tasks to measure the difference between probability distributions and penalize inaccurate predictions.

Table 3.1: Application of Loss Functions

The mathematical formula for Binary Cross-Entropy Loss, or Log Loss, is:

$$L(y, f(x)) = -[y \log(f(x)) + (1 - y) \log(1 - f(x))]$$

Where:

- L represents the Binary Cross-Entropy Loss function
- y is the true binary label (0 or 1)
- $f(x)$ is the predicted probability of the positive class (between 0 and 1)

3.2.1.3 Optimizers

Deep learning algorithms employ optimization methods aimed at minimizing or maximizing an objective function, often referred to as a cost function or loss function.

During the training of a deep neural network with a dataset, the objective is to identify optimal parameters (θ) that effectively reduce the cost function $J(\theta)$ [33]. An optimizer, whether in the form of a function or algorithm, is responsible for adjusting the attributes of a neural network, such as weights and learning rates. Its primary objective is to minimize the overall loss and enhance accuracy. Given that a deep learning model typically comprises millions of parameters, determining the appropriate weights can be a challenging task. Therefore, selecting a suitable optimization algorithm for a specific application becomes crucial. Some of the most used optimizers are :

1. Stochastic Gradient Descent (SGD): This algorithm is widely utilized in both machine learning and deep learning for optimization purposes. It adjusts the model parameters (weights) by computing the gradient of the loss function on a randomly selected subset of the training data, which is referred to as a mini-batch. This process is repeated iteratively until convergence or a stopping criterion is met. SGD offers advantages like faster convergence, lower memory requirements, and robustness to noisy data. However, tuning the learning rate is crucial for ensuring convergence.

2. Momentum: It is a technique used in machine learning to speed up the training of neural networks. It involves adding a fraction of the previous weight update to the current update during optimization. By accumulating past gradients, momentum helps smooth out the optimization process and prevents the optimizer from getting stuck in local minima. This technique is particularly effective in noisy or rapidly changing optimization landscapes, leading to faster convergence and improved performance of deep neural networks.

3. AdaGrad:AdaGrad is a machine learning optimisation approach that uses previous gradients to dynamically modify the learning rates for each parameter. The learning rate is inversely related to the square root of the total squared gradients when using this method. Large gradient parameters hence receive lower learning rates, which encourage quicker convergence. With its ability to effectively handle low-frequency or missing input features, it is particularly useful for sparse data. Hence, it's a strong optimisation method to improve deep neural network performance. The aggressive and monotonically declining learning rate of it is one of its drawbacks. Over time, the learning rate

gets progressively smaller as the squared gradients build up in the denominator. This could impair the model's capacity to learn new information and jeopardise its accuracy.

4. RMSProp: RMSProp computes a moving average of squared gradients to modify learning rates. By smoothing modifications, it avoids the quick decline in learning rate that Adagrad causes. In order to give preference to more recent gradients over older ones, the method includes a decay factor. RMSProp is particularly good in managing non-stationary objectives and operates well under change. It's a strong optimisation method to improve deep neural network performance. The issue with RMS Prop is that not all applications can use the recommended value, and the learning rate must be explicitly defined. RMS Prop faces challenges while handling big datasets and running updates in small batches.

5. Adam: The Adam optimizer, derived from Adaptive Moment Estimation, is a popular optimization algorithm in deep learning. It modifies learning rates for each weight dynamically, leveraging gradient history and second moment information. By integrating elements from AdaGrad and RMSProp, Adam efficiently updates neural network weights during training. Its adaptive learning rate adjustments make it highly effective across a range of deep learning applications, facilitating quicker convergence and enhanced model performance compared to conventional methods such as stochastic gradient descent.

3.3 Long Short Term Memory (LSTM)

Long Short-Term Memory (LSTM) is the variant of Recurrent Neural Networks (RNNs) specifically tailored to capture prolonged relations in sequential data. Unlike traditional RNNs, LSTMs excel in processing and interpreting sequential data types such as time series, text, and speech by effectively managing challenges associated with long short-term memory. LSTMs address this complexity through two primary functions: discarding unnecessary context information and integrating potentially valuable data for future decision-making. Instead of embedding a rigid strategy within their architecture, LSTMs dynamically adapt to efficiently handle context.

To accomplish this, LSTMs incorporate an additional context layer within their architecture, alongside the recurrent hidden layer. These networks use specialized neural units with gates that control the flow of information between network layers.

The gates in an LSTM employ extra weights that interact in sequence with the input, the previous hidden layer, and the previous context layers. Each gate follows a typical design pattern: it includes a feedforward layer, applies a sigmoid activation function, and then performs pointwise multiplication with the layer it gates. The sigmoid activation function is selected for its ability to drive outputs towards values close to 0 or 1. When integrated with pointwise product, this mechanism operates akin to a binary mask. Elements within the gated layer that correspond to positions where the mask approaches 1 remain largely unaltered, whereas elements corresponding to lower mask values are effectively attenuated or suppressed [34].

1. **Forget Gate**: Its main purpose is to remove unnecessary information from the context. It computes a weighted combination of the preceding hidden state and the current input.This combination (sum) undergoes a sigmoid activation to create a filter. This filter is then applied element-wise to the context vector, enabling the LSTM to selectively preserve or discard details from the context that are no longer pertinent to the ongoing computation. The element-wise product of the two vectors, denoted by the symbol $\odot$, yields a vector with the same dimensionality as the initial input vectors. Every component i in the resulting vector is computed as the product of the corresponding elements i from the input vectors. This operation allows for simultaneous multiplication of corresponding components across the vectors.

$$f_t = \sigma(U_f h_{t-1} + W_f x_t) \tag{3.1}$$

$$k_t = c_{t-1} \odot f_t \tag{3.2}$$

The next step entails calculating essential information to be extracted from both the previous hidden state and current inputs, a foundational computation employed across all recurrent networks:

$$g_t = \tanh(U_g h_{t-1} + W_g x_t) \tag{3.3}$$

Subsequently, the next step involves generating a filter for the addition gate, which determines the details to be incorporated into the ongoing context:

$$i_t = \sigma(U_i h_{t-1} + W_i x_t) \tag{3.4}$$

$$j_t = g_t \odot i_t \tag{3.5}$$

To create the new context vector, we then append this altered context vector:

$$c_t = j_t + k_t \tag{3.6}$$

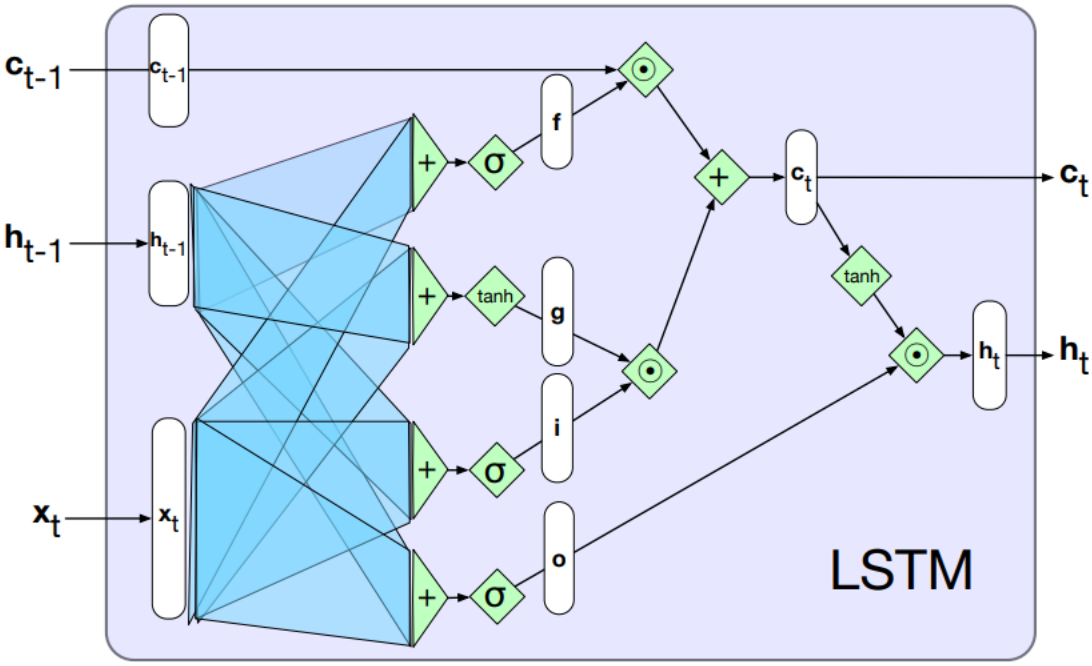

Figure 3.10: Long Short Term Memory [34]

2. **Output Gate**: This is the final gate that distinguishes between the information relevant to the present state and the details that should be kept for future use:

$$o_t = \sigma(U_o h_{t-1} + W_o x_t) \tag{3.7}$$

$$h_t = o_t \odot \tanh(c_t) \tag{3.8}$$

Figure 3.10 illustrates the entire computation process for an LSTM unit. Each unit receives inputs consisting of the current input vector x, previous context c_{t-1} and the preceding hidden state h_{t-1}. Outputs include a latest hidden state h_t and a revised context c_t. With appropriate weights for the gates, an LSTM processes the context and hidden layers from the previous time step along with the current input, generating updated context and hidden vectors as outputs. The hidden state h_t serves as the LSTM's output at each time step, which can then be used as input to subsequent layers in a multilayered RNN or as the final output of the LSTM in the network's final layer.

3.4 Deviation Settlement Mechanism

In the context of electricity trading, "deviation" for a seller refers to the difference between its total actual power injected and its scheduled injection. For a buyer, deviation means the difference between its total actual power drawn and its scheduled drawl.

(1) Deviation in a time block for buyers is computed as follows:

- Deviation within a time block for buyers is determined as follows:
  - Deviation for buyers (in MWh) = Actual drawl (MWh) - Scheduled drawl (MWh)
  - Deviation for buyers (in %) = 100 × [Actual drawl (MWh) - Scheduled drawl (MWh)] / Scheduled drawl (MWh)
- Deviation within a time block for sellers is calculated as:
  - Deviation for sellers (in MWh) = Actual injection (MWh) - Scheduled injection (MWh)
  - Deviation for sellers (in %) = 100 × [Actual injection (MWh) - Scheduled injection (MWh)] / Scheduled injection (MWh)

CHAPTER FOUR: SYSTEM MODEL & PROBLEM FORMULATION

In this chapter, the system model considered for DAM and RTM bidding, DSM for the study, and problem formulation to minimize the energy trading cost is presented.

4.1 System Model

4.1.1 Market Model: Nepal and IEX

DAM bidding takes place one day prior to the delivery day, while the RTM operates closer to real-time. In IEX specifically, there is a 30-minute interval between two RTM transactions, with the gate closing one hour before delivery operating 48 times a day, with delivery occurring in two 15-minute time blocks. DAM establishes initial trading plans based on forecasts. However, deviations often occur due to unpredictable factors such as weather fluctuations and unforeseen events. These deviations necessitate real-time adjustments to maintain grid stability and economic efficiency. RTM bidding, operating closer to actual delivery times, plays a crucial role in mitigating forecasting errors by responding promptly to changes in supply and demand. Nepal currently participates in the DAM and RTM of the IEX through the Dhalkebar-Muzzaffarpur $400KV$ transmission line and Tanakpur-Mahendranagar $132KV$ line. To effectively minimize the deviation costs and maximize revenue, time series prediction model are essential for accurately predicting imports across DM and TM lines, and RTM MCP for bidding in RTM. Variability in generation and demand due to factors like weather, holidays, and inaccurate load forecasting methods often lead to significant deviations from scheduled operations. These deviations result in high DSM charges. Improving load, generation, and import forecasting accuracy is therefore crucial to minimizing deviations and associated DSM charges in the DAM and RTM.

4.1.2 DSM Model

In the context of electricity trading, "deviation" for a seller refers to the difference between its total actual power injected and its scheduled generation. For a buyer, deviation means the difference between its total actual power drawn and its scheduled drawl. The deviation in a time block for buyers is computed as follows:

- Deviation (MWh) = Actual drawl - Scheduled drawl

- Deviation % = 100× $\big($Actual drawl (MWh) - Scheduled drawl in MWh$\big)$ / Scheduled drawl (MWh)

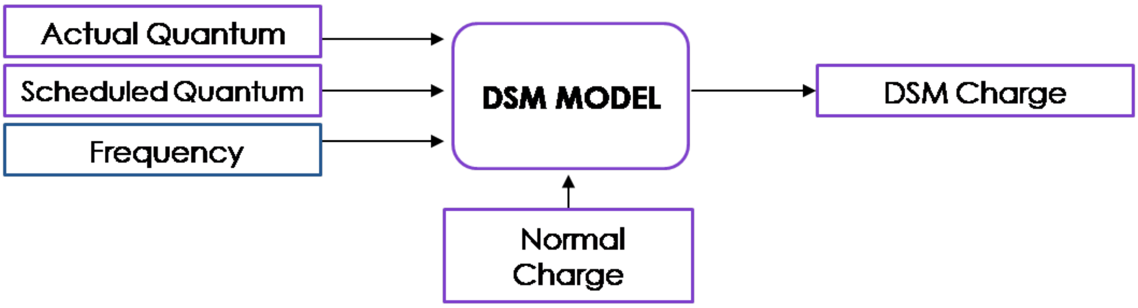

Figure 4.1: DSM Model

Based on the CERC guidelines [17] as highlighted in Figs. 4.1-4.4, Nepal's deviation from scheduled quantum can be modeled into following four scenarios based on the difference between actual and scheduled quantum and MW limits:

Scenario 1: Overdrawl by Buyer

If the frequency (f) is below 49.95 Hz, the buyer incurs charges for deviation based on the following rates:

- 150% of the normal charges of deviation (NCD) when $49.90 < f < 49.95$
- 200% of the NCD when $f < 49.90$

If the frequency (f) exceeds 50.03 Hz, the buyer faces deviation charges as follows:

- 75% of the NCD when $50.03 > f > 50.05$
- Zero charges when $f \geq 50.05$

Scenario 2: Underdrawl by Buyer

If the frequency (f) is below 49.95 Hz, the buyer is reimbursed for deviation based on the following rates:

- 120% of NCD if $49.90 < f < 49.95$
- 150% of NCD if $f < 49.90$

Entity	**Charges for deviation payable to Deviation and Ancillary Service Pool Account**	
Seller	**Deviation by way of over injection**	**Deviation by way of under injection**
For a general seller other than an RoR generating station or a generating station based on municipal solid waste	Zero: Provided that such seller shall be paid back for over injection up to @ the reference charge rate for deviation up to [10% Deviation-general seller or 100 MW, whichever is less].	(i) @ the reference charge rate up to 10% deviation general seller or 100 MW whichever is less]: (ii) 120% of the normal rate of charges for deviation by way of under injection beyond [10% deviation general seller or 100 MW, whichever is less] and up to [15% deviation general seller or 150 MW, whichever is less]; (iii) @150% of the normal rate of deviation beyond [15% deviation general seller or 150 MW, whichever is less].

Figure 4.2: Seller DSM

Entity	**Charges for deviation payable to Deviation and Ancillary Service Pool Account**	
Buyer	**Deviation by way of under drawl**	**Deviation by way of overdrawl**
Buyer (with schedule up to 400 MW)	Zero: Provided that such buyer shall be paid back for under drawl @ 90% of normal rate of charges for deviation up to [20% Deviation-buyer (in %) or 40 MW Deviation buyer (in MWh) in a time block, whichever is lower].	(i) @ normal rate of charges for deviation up to [20% Deviation-buyer (in %) or 40 MW Deviation-buyer (in MWh) in a time block, whichever is lower]; and (ii) @120% of normal rate of charges for deviation beyond [20% Deviation-buyer (in %) or 40 MW Deviation-buyer (in MWh) in a time block, whichever is lower].

Figure 4.3: Buyer with schedule up to 400MW

Entity	**Charges for deviation payable to Deviation and Ancillary Service Pool Account**	
Buyer	**Deviation by way of under drawal**	**Deviation by way of over drawal**
Buyer (other than the buyer with schedule less than 400 MW and the RE-rich State)	Zero: Provided that such buyer shall be paid back for under drawal as under: (i) @ 90% of normal rate of charges, for deviation up to [*10% D_{BUY} or100 MW, whichever is lower*]; (ii) @ 50% of normal rate of charges, for deviation beyond [*10% D_{BUY} or 100 MW, whichever is lower*] and up to [*15% D_{BUY} or 200 MW, whichever is lower*].	(i) @ normal rate of charges for deviation up to [*10% D_{BUY} or 100 MW, whichever is lower*]; (ii) @120% of normal rate of charges for deviation beyond [*10% D_{BUY} or 100 MW D_{BUY}, whichever is lower*] and up to [*15% D_{BUY} or 200 MW, whichever is lower*]; and (iii) @150% of normal rate of charges for deviation beyond [*15% D_{BUY} or 200 MW, whichever is lower*].

Figure 4.4: Buyer with schedule more than 400MW

If the frequency (f) exceeds 50.03 Hz, the buyer is reimbursed for deviation at the rate of:

- 50% of NCD if $50.03 > f > 50.05$
- Zero if $f \geq 50.05$

Scenario 3: Underinjection by Seller

If the frequency (f) is below 49.95 Hz, the seller shall pay

- 150% of the reference charge rate (RCR) or 120% of the NCD, whichever is higher, in the following cases when $49.90 < f < 49.95$
- 200% of the RCR or 150% of the NCD, whichever is higher, if $f \leq 49.90$ Hz.

If the frequency (f) is greater than 50.03 Hz, the seller pays for deviation at the following rates:

- 75% of the RCR for $50.03 < f < 50.05$
- 50% of the RCR when $f \geq 50.05$.

Scenario 4: Overinjection by Seller

If the frequency (f) is less than 49.95 Hz, the seller shall pay

- 120% of the RCR when $49.90 < f < 49.95$
- 150% of the RCR if $f \leq 49.90$ Hz.

If the frequency (f) is greater than 50.03 Hz, the seller pays for deviation at the following rates:

- 50% of the RCR for $50.03 < f < 50.05$
- zero when $f \geq 50.05$.

Nepal has been listed as buyer so the overdraw and underdrawl conditions will be applied for calculating DSM charge.

4.2 Problem Formulation

Based on the system model discussed in previous section, the problem formulation for the study is presented in this section.

For any time instant t, the objective of the problem is to place the optimal bids so as to minimize the total cost of trading energy through the IEX interfaces over a time horizon T. Since we allow the bidding energy to be both positive and negative, the formulation equally works in the case of exporting energy to IEX as well as importing energy from IEX. We consider the amount of energy bid at any time instant t over an IEX-Nepal energy interface i to be $e_{i,t}\Delta t$ where $e_{i,t}$ is the power and Δt is the time period of importing/exporting that power at time t through the interface i. Since Nepal participates in energy exchange through two interfaces at the moment i.e. Dhalkebar and Tanakpur interfaces, the set of Interfaces $\mathcal{S}$ consists of these two interfaces only. Similarly, the price at which Nepal bids these energy through a given interface i at a time instant t is given by $\rho_{c,t}$ that are bounded by the minimum and maximum price caps ρ_{min} and ρ_{max}. The overall load of Nepal and power generation at a time instant t is given by $P_{L,t}$ and $P_{G,t}$. Total imports from rest of the interfaces with India other than Dhalkebar and Tanakpur is considered to be $E_{O,t}$. The problem formulation for the optimal bidding for trading energy with IEX is presented as follows.

$$
\begin{aligned}
\text{minimize} \quad & \sum_{t\in\mathcal{T}}\sum_{i\in\mathcal{S}} e_{i,t}\Delta t\rho_{c,t} && && (4.1)\\
\text{s.t.} \quad & \alpha P_{L,t} \le \sum_{i\in\mathcal{S}} e_{i,t} + E_{O,t} + P_{G,t} \le P_{L,t}, \text{ if } P_{G,t} \le P_{L,t}, && \forall t && (4.1a)\\
& P_{L,t} - P_{G,t} \le \sum_{i\in\mathcal{S}} e_{i,t} \le 0, \text{ if } P_{G,t} > P_{L,t}, && \forall i,t && (4.1b)\\
& |e_{i,t}| \le P_i, && \forall i,t && (4.1c)\\
& e_{i,t} + \sum L_{i,t}^{(in)} = \sum L_{i,t}^{(out)}, && \forall i,t && (4.1d)\\
& \rho_{min} \le \rho_{c,t} \le \rho_{max}, && \forall w_i, s_j && (4.1e)
\end{aligned}
$$

We present the objective function of our problem in Eq. (4.1) that aims to minimize the total cost of trading energy with India through IEX while also trying to limit the total interruption. Constraint (4.1a) requires the sum of total generation and total imports to be within the acceptable range of load demand we want to meet whenever the load demand is higher than the generation. This is modeled using the interruption factor $\alpha \in [0, 1]$ that represents the fractional amount of load that must be met. Similarly, in constraint (4.1b), the sum of total bidding exports need to be less than 0 and greater than the difference between load demand and generation whenever generation is higher than the load demand. In other words, export is modeled as negative value and therefore minimizing the cost would translate to maximizing the revenue. We also put the flow limit of line joining the interface i with IEX in constraint (4.1c) to not exceed the P_i and the total flow through those interfaces in (4.1d) by setting all the incoming flow equal to outgoing flow at all time t. Finally the bidding price caps are put in place using the minimum and maximum bid price ρ_{min} and ρ_{max}.

CHAPTER FIVE: METHODOLOGY & SOLUTION APPROACH

5.1 Data Collection

Dataset on load, generation, interruptions, and imports (specifically from DM,TM, and other sources) spanning from March 2021 to March 2024 were collected from log sheets maintained by operators at the Load Dispatch Center (LDC). Additionally, weather-related data including temperature, rainfall, relative humidity, cloud cover, wind speed, day, some river discharge and sunshine duration for the same period were sourced from Open-Meteo, an open data platform. Furthermore, significant line loading data such as Dhalkebar-Mirchaya, Dhalkebar-Khimti, Dhalkebar substation, and Dhalkebar-Nawalpur were extracted from the SCADA system. The frequency of data collection varied, with some data being recorded hourly, half-hourly, and others at 15-minute intervals. Additionally, information regarding holidays in Nepal was obtained from open sources. Furthermore, data related to MCP on the IEX was collected from the IEX website.

We carefully selected the features and target variables crucial for our regression analysis. The features chosen encompass various factors believed to influence our target variables, including temporal attributes such as year, month, and day, alongside meteorological conditions like temperature, rainfall, relative humidity, cloud cover, wind speed, some of the river discharge and sunshine duration. Additionally, indicators of holidays and historical data on imports, generation, and load were incorporated as features to capture potential correlations. Simultaneously, our target variables were meticulously chosen to represent key aspects of Load, generation, import, and MCP. After extracting these features and target variables from our dataset, we ensured consistency in the number of samples and performed essential data preprocessing steps. We partitioned the dataset into training and testing subsets using a conventional 80-20 split, with 80 percent of the data used for training and 20 percent for testing. This division ensures a substantial portion of data is utilized for training the model, while also preserving a representative subset for evaluating its performance on unseen data.

A Deep Neural Network (DNN) model is initialized using PyTorch for regression tasks. The DNN model is created with fully connected layers, the ReLU activation functions, and dropout regularization. The model architecture is defined with four hidden layers containing 512, 256, 256, and 132 neurons, respectively. The input size is determined by the number of features in the training data, while the output size corresponds to the number of target variables. Additionally, we set a random seed for reproducibility and specify the keep probability for dropout regularization. For training the model, we define the loss function using the Huber Loss, which is robust to outliers and suitable for regression tasks. The optimizer is initialized with the Adam optimization algorithm, configured with a learning rate of 0.001. The optimizer is responsible for updating the parameters of the DNN model during the training phase to minimize the defined loss function and improve the model's performance.

Following the training and testing phases, the model's production phase commenced for the month of January 2024 and for the month of March 2024 as well. During this phase, the trained model was deployed to forecast load, generation and import for the specified period. Utilizing this solution, the import from DM was also determined as part of the overall forecast. This is considered as the model depicting the schedule to be taken for the DAM Model.

Furthermore, actual and scheduled import from DM and TM, deviation, normal charges of deviation, frequency, data were sourced from both the Eastern Region Power Committee website and partially from the National Load Dispatch Center, India (NLDC) website. These datasets are provided in a 15-minute time format, which is crucial for our forecasting purposes as it aligns with the bidding format requirements. In our scenario, we leveraged Long Short-Term Memory (LSTM) networks for predicting future values in a time series. LSTMs are well-suited for this task due to their ability to capture relationships between past and future values effectively. Moreover, they exploit the advantages of RTM, enabling us to place bids 1 hour and 15 minutes in advance. By utilizing actual import data via DM, the LSTM model predicts the import values required for bidding in the RTM. This approach ensures that our bidding strategy aligns closely with RTM dynamics, enhancing our ability to make timely and informed decisions.

5.2 Solution Approach

The optimization problem in equation (4.1) requires knowledge of the estimated generation $P_{G,t}$, estimated load $P_{L,t}$, and estimated import $e_{i,t}$, which can be predicted using regression analysis and time series forecasting. This predictive information helps determine the level of energy to be traded through the IEX interfaces based

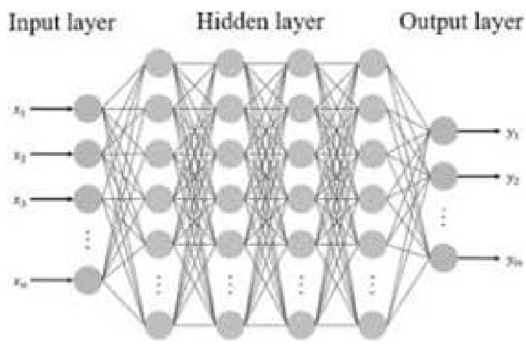

Figure 5.1: DNN Model Architecture

on generation and demand imbalances and line loading levels. The simplified solution approach is outlined below.

Given their proven success in forecasting and time series prediction, we utilize deep learning in our application. Deep Neural Networks (DNNs) have an inherent capability to autonomously identify patterns and extract features from datasets with numerous input variables, making them highly suitable for regression tasks.

5.2.1 DNN Model

Deep neural network (DNN) models excel in multivariate time series forecasting due to their ability to handle nonlinear dependencies, complexity, and high-dimensional data. We used a fully connected DNN model for its effectiveness in regression analysis, particularly in predicting variables like load, generation, and import based on historical and weather data. By capturing complex relationships and automatically extracting relevant features, these networks offer a robust framework for Day-Ahead Market (DAM) bidding, enabling accurate forecasts of load, generation, and import.

5.2.2 LSTM Model

Long Short-Term Memory (LSTM) networks, a type of Recurrent Neural Network (RNN), are ideal for capturing long-term dependencies in sequential data, overcoming challenges like vanishing or exploding gradients. In this work, LSTMs are employed for RTM bidding due to their ability to selectively remember and forget information. By training on historical import/export data from DM & TM and RTMCP, LSTMs enhance bidding strategies by identifying complex relationships and recurring patterns. This results in precise predictions of future import/export values and RTMCP, crucial for effective RTM bidding in energy markets.

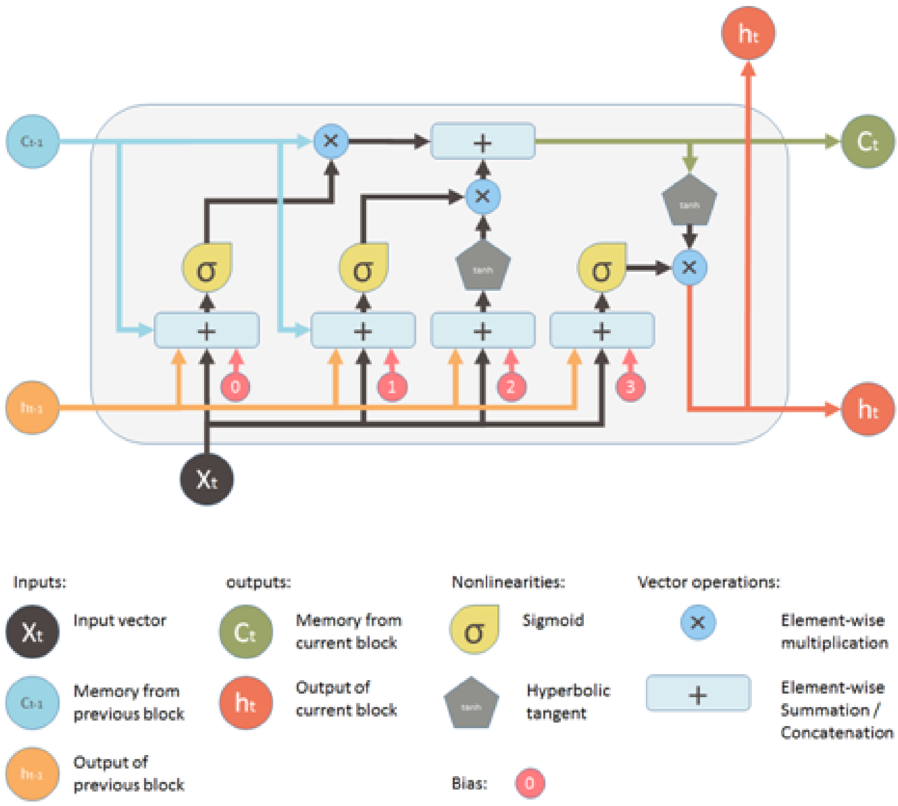

Figure 5.2: LSTM Model Architecture

5.2.3 DSM Model

Currently registered as a buyer, Nepal encounters four specific conditions, which are outlined below and illustrated in the flowchart from Figs. 5.3- 5.6.

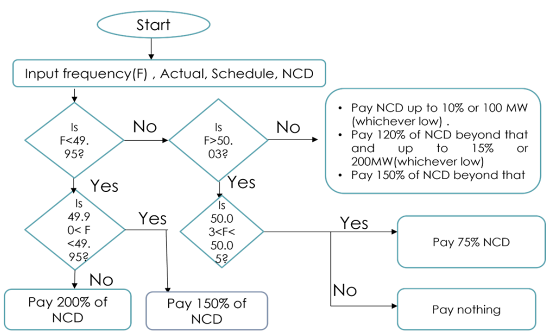

Figure 5.3: Overdraw more than 400MW

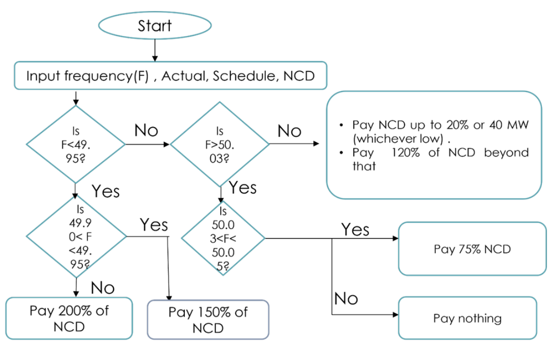

Figure 5.4: Overdraw up to 400MW

- Overdraw with schedule more than 400 MW (Fig. 5.3)
- Overdraw with schedule up to 400 MW (Fig. 5.4)
- Underdraw with schedule more than 400 MW (Fig. 5.5)

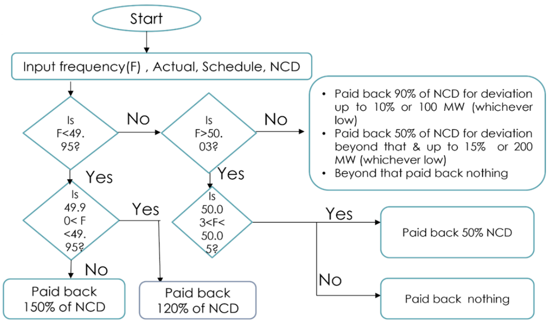

Figure 5.5: Underdraw more than 400MW

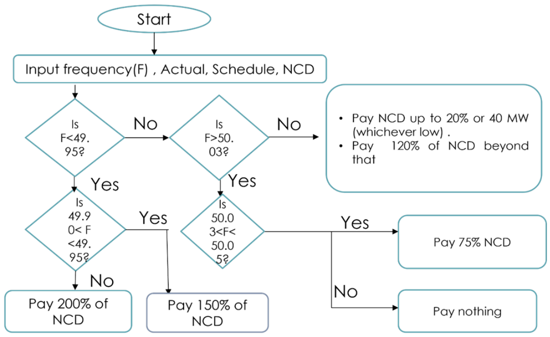

Figure 5.6: Underdraw up to 400MW

- Underdraw with schedule up to 400 MW (Fig. 5.6)

According to CERC guidelines, the presented DSM model computes DSM charges, whether payable or receivable, based on inputs such as actual and scheduled quantum, frequency, and normal charges of deviation (NCD).

5.2.4 Heuristic Algorithm for DAM and RTM bidding (HeADR)

A heuristic-based algorithm is presented in Algorithm 5.1. This algorithm optimizes bidding strategies in Nepal's electricity market for both the DAM and RTM using deep learning models. It takes into account weather data, the previous day's generation and load, previous day's import, and scheduled imports to predict generation, load, MCP, and imports from DM and TM using a DNN model (line 1). These forecasts rely on weather data, the previous day's operational data, and planned imports.

Subsequently, for each time interval $t \in \mathcal{T}$, the algorithm adjusts and limits the import from Tanakpur based on constraint violations (line 3). The import from Dhalke is then calculated as the balance between load, generation, scheduled imports, and Tanakpur imports (line 4). The results are further refined to adhere to predefined constraints (Eq. (1a)-(1e)). Bids are then submitted in the DAM based on the computed imports from Dhalke and Tanakpur (line 9).

Algorithm 5.1: Heursitic based Algorithm for DAM and RTM bids

Input : Weather data ($\mathcal{W}$), Prev-day-Generation (P_G^{prev}), Prev-day-Load (P_L^{prev}), Prev-day-Import, Scheduled Import E_O

Output: Generation P_G, Load P_L, MCP (ρ_c), Import from Dhalke (e_1), Import from Tanakpur (e_2)

1 $P_L, P_G, \rho_c, e_2 = DNN(\mathcal{W}, P_G^{prev}, P_L^{prev}, E_O)$;
2 **for** *each* $t \in \mathcal{T}$ **do**
3     $e_2 = clip(e_2, P_2)$;
4     $e_1 = P_L - P_G - E_O - e_2$;
5   Clip the output;
6   Check for constraintsin Eqs. (4.1a) - (4.1e);
7   Adjust the output;
8 **end**
9 Place bids in DAM with e_1 and e_2;
10 $[e_1^{t+1}, e_1^{t+7}], [e_1^{t+1}, e_1^{t+7}], [\rho_{c,t+1}^{RTM}, ..., \rho_{c,t+7}^{RTM}] = LSTM([e_1^{t-16}, e_1^t], [e_2^{t-16}, e_2^t], [\rho_{c,t-16}^{RTM}, \rho_{c,t}^{RTM}])$;
11 **for** *each* $t \in (0, T, 2)$ **do**
12     $e_2 = clip(e_2, P_2)$;
13   Clip the output;
14   Check for constraints in Eqs. (4.1a) - (4.1e) ;
15   Adjust the output;
16   Place bids in RTM with $e_{1,t+6:t+7}$ and $e_{2,t+6:t+7}$;
17 **end**

For real-time bidding, the HeADR algorithm employs an LSTM model to predict imports and RTMCP for upcoming time intervals using data from the past 16 time steps (line 10). In the RTM, import predictions for DM $400KV$ and TM $132KV$ lines are adjusted and bounded based on constraints similar to those used in the DAM (lines 11-17). Following the forecasted values, bids are then placed in the RTM. This heuristic-based approach ensures optimal bidding strategies in both DAM and RTM by leveraging advanced deep learning models, thereby enhancing forecasting accuracy, minimizing deviation costs, and ensuring grid stability.

CHAPTER SIX: RESULTS AND DISCUSSION

6.1 System, Tools and Metrics

6.1.1 System Considered

A Deep Neural Network (DNN) model is developed for trading in the Day-Ahead Market. Additionally, an LSTM model is implemented for bidding in the RTM. Also, a DSM Model as per CERC guidelines is developed in python which will be used for further analysis. The analysis will focus on the charges incurred by Nepal due to variations in scheduled trading, and will also explore how deviation charges vary with Nepal's participation in the RTM. The primary objective is to minimize these deviation charges once the relationships are fully understood.

6.1.2 Tools and Software

Advances in computer architecture and software have greatly simplified power system modeling and analysis, which were previously difficult, time-consuming, and often inaccurate. Modern software tools use mathematical models to simulate power system performance effectively. This thesis utilizes Python, Excel, and LaTeX.

- **Python:** Python is a sophisticated, object-oriented, and dynamically interpreted programming language known for its modular design and reusable code. It comes with a comprehensive standard library and is freely available for all major platforms in both source and binary forms. In our thesis, we utilized the PyTorch library, specifically its 'torch.nn' module, to build and train neural networks. For handling and analyzing data, we turned to the Pandas library, which made it easy to clean, explore, and analyze datasets. Additionally, we made use of the NumPy library for efficient array operations. In the field of machine learning, we took advantage of scikit-learn ('sklearn'), a robust Python library that offers a wide range of tools for preprocessing data, developing models, and evaluating them. For visualization purposes, we relied on the matplotlib library, which enabled us to create informative plots and graphs.

- **Excel:** Microsoft Excel, a spreadsheet program created by Microsoft for use on Windows, Android, iOS, and macOS platforms, provides functionalities like computational tools, graphing capabilities, pivot tables, and a macro programming environment known as Visual Basic for Applications (VBA). Excel is a part of the Microsoft 365 suite of software. In our thesis, Excel played a crucial role in collecting data from various sources and compiling it. Additionally, it was used to save the compiled data as CSV files, which were later utilized in Pandas for further analysis.

- **LaTeX:** In LaTeX, we structured our report effectively, ensuring clear and automatically numbered complex mathematical equations. LaTeX enabled precise placement and captioning of figures and tables, facilitated the clear presentation of algorithms, and streamlined citation management using BibTeX. Overall, LaTeX enhanced the professionalism and clarity of our report and paper, establishing it as an indispensable tool for report writing.

6.1.3 Metrics Utilized

Test Loss

The test loss is computed as the difference between predicted outputs and actual target values on a dataset that was not utilized during the model's training phase. The main purpose of test loss is to evaluate the model's capability to generalize to new, unseen data. Evaluating test loss is crucial to ascertain if the model has successfully learned patterns that extend beyond the data it was trained on. In real-world scenarios, reduced test loss signifies improved accuracy in predicting outcomes, provided that the test dataset adequately represents the complexity and diversity found in the data the model is intended to manage.

R^2 score

The R^2 score is crucial for assessing model accuracy by quantifying how well it predicts the dependent variable's outcomes. Ranging from 0 to 1, where 0 means no predictive power and 1 means perfect prediction, R^2 measures how much of the variability in the dependent variable's values the model can explain. Higher R^2 scores indicate better alignment between predicted and actual values, reflecting stronger predictive performance and suitability for real-world applications.

6.2 Model Performance and Simulation

Data spanning from March 2021 to March 2024 was collected from multiple sources: Generation, load, scheduled import and interruption data from Nepal Electricity Authority Load Dispatch Center daily logsheets, weather data via Open-Meteo, SCADA system for line loading, and open sources providing holiday and Market Clearing Price (MCP) information.

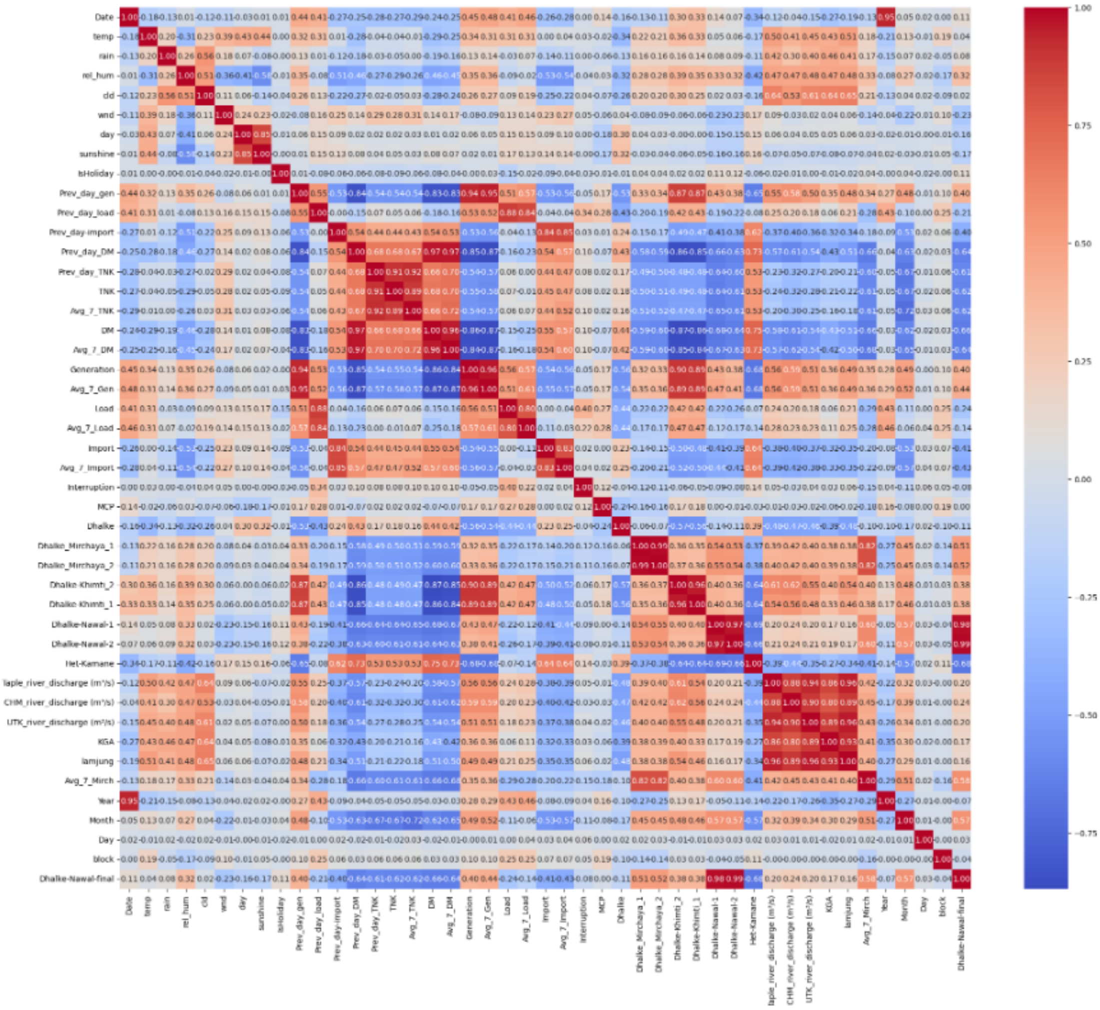

Figure 6.1: Correlation between target and features

Dataset for DNN, LSTM and algorithm was prepared through thorough data preprocessing and manipulation to bring all of them into the same resolution and workable. To prepare the dataset for DNN model, careful feature selection was also conducted based on correlations and variance as depicted in Fig. 6.1. Historical data on imports, generation, and load were also incorporated as features to capture potential correlations with the target variables.

6.2.1 DAM Bidding with DNN Model

The dataset was partitioned into training and testing subsets using an 80-20 split, ensuring that a significant portion of the data was utilized for training the model while preserving a representative subset for evaluating its performance on unseen data. For regression tasks, a Deep Neural Network (DNN) model was initialized using PyTorch library with 4 hidden layers of size $512 \times 256 \times 256 \times 132$,Huber Loss function, and Adam optimizer. The neural network was configured to undergo training for 80 epochs, wherein each epoch represents a complete pass through the entire training dataset. During training, data was processed in batches, with 16 samples per batch utilized for training and 96 samples per batch used for testing. This batch size strategy allows for efficient computation and optimization of the network's parameters. The learning rate, a hyperparameter that dictates the step size at which the model's parameters are updated during optimization, was set to 0.001. 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. Momentum helps accelerate the optimization process by accumulating the gradient of past iterations, thus allowing for smoother and faster convergence towards the optimal solution. Furthermore, a keep probability of 1 was set for dropout regularization, indicating that all neurons were retained during training. The random seed used for initialization and training of the neural network was set to 42. Setting a random seed is essential for ensuring consistent outcomes. It establishes the initial state of the random number generator, ensuring that the code produces the same sequence of random numbers with each execution.

Table 6.1: DNN Model Table

Hyperparameter	**Description**
Split ratio (training/testing)	80-20
Number of epochs	80
Batch size (training)	16
Batch size (testing)	96
Learning rate	0.001
Momentum	0.5
Keep probability (dropout)	1
Random seed	42
Neural network architecture	4 hidden layers: 512, 256, 256, 132 neurons
Loss function	Huber Loss
Optimizer	Adam

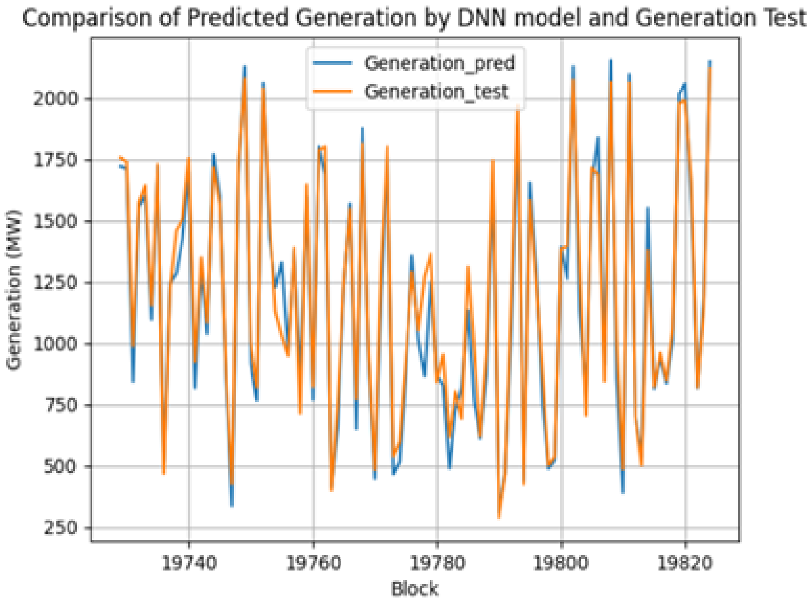

Figure 6.2: Generation Predicted by DNN value vs Test

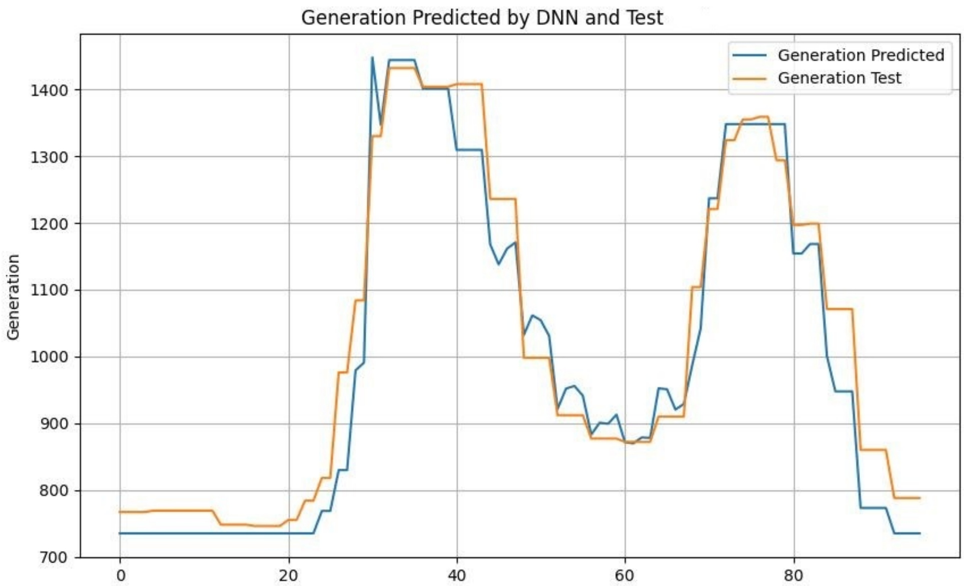

Figure 6.3: Generation Predicted by DNN model vs Test for blocks

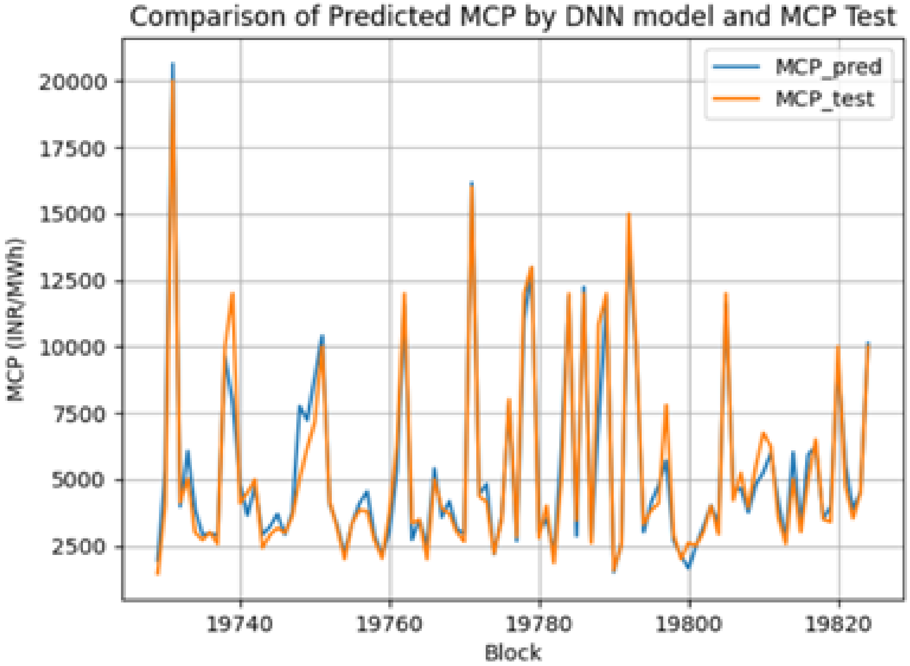

Figure 6.4: MCP predicted by DNN Model as per blocks

The input layers, along with the hidden and output layers, together constitute the network's architecture, enabling it to comprehend intricate patterns and relationships within the input data. For the optimization process during training, the Huber Loss function was chosen as the loss function. The Huber Loss is robust to outliers and strikes a balance between the Mean Absolute Error (MAE) and Mean Squared Error (MSE) loss functions, making it suitable for regression tasks. To optimize the model parameters, the Adam optimizer was employed. Adam is an adaptive optimization algorithm that computes individual learning rates for each parameter based on their past gradients and squared gradients, enabling efficient and effective optimization of the neural network parameters.

Table 6.2: DNN Model Accuracy

Parameter	Description
Model Accuracy (Generation)	96%
Model Accuracy (Load)	90%
Model Accuracy (MCP)	92%
Model Accuracy (Tanakpur Import)	87%

Overall, this configuration of hyperparameters, 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 during

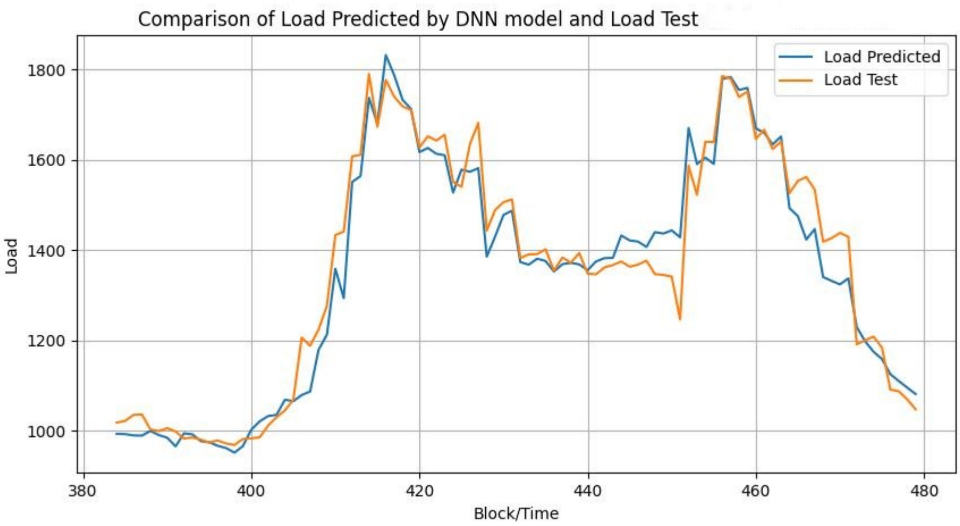

Figure 6.5: Load Predicted by DNN model Vs Test

the production phase of the model. After the training and testing phases, the model transitioned into the production phase for data of January 2024 and for March 2024 as well. Here, the trained model was deployed to forecast load, generation, and imports for the designated period. Specifically, the import from DM and TM was determined as a key aspect of the overall forecast, aligning with the prerequisites of the DAM Model. During the testing phase, the accuracy of the model was calculated using the coefficient of determination, R^2 score and is summarised in Table 6.2.

Fig. 6.2 displays the predicted generation values in MW from the DNN model alongside the actual values. Since bidding is conducted in 15-minute intervals, totaling 96 blocks per day, we also analyzed the average generation predictions blockwise. Fig. 6.3 shows that the predicted values closely align with the actual values, indicating that the DNN model provides accurate forecasts in both cases. Fig. 6.4 compares the Market Clearing Price (MCP) in INR/MWh predicted by the DNN model with the actual MCP. This comparison highlights the precise performance of the DNN model to predict MCP. Fig. 6.5 demonstrates the DNN model's effectiveness in accurately forecasting load. Fig. 6.6 and Fig. 6.7 also shows the blockwise average value of the import solution for Tanakpur-Mahendranagar (TM) and Dhalkebar-Muzzaffarpur (DM) provided by DNN model. The predicted and test values comparison are shown in the figure. Similarly, we can see the average value blockwise predicted by the model and its comparison with test in the Fig. 6.6, 6.7, 6.9 and 6.10 for the month of January 2024. With proper forecasting of load and generation, the interruption can be reduced as shown in Fig. 6.8.

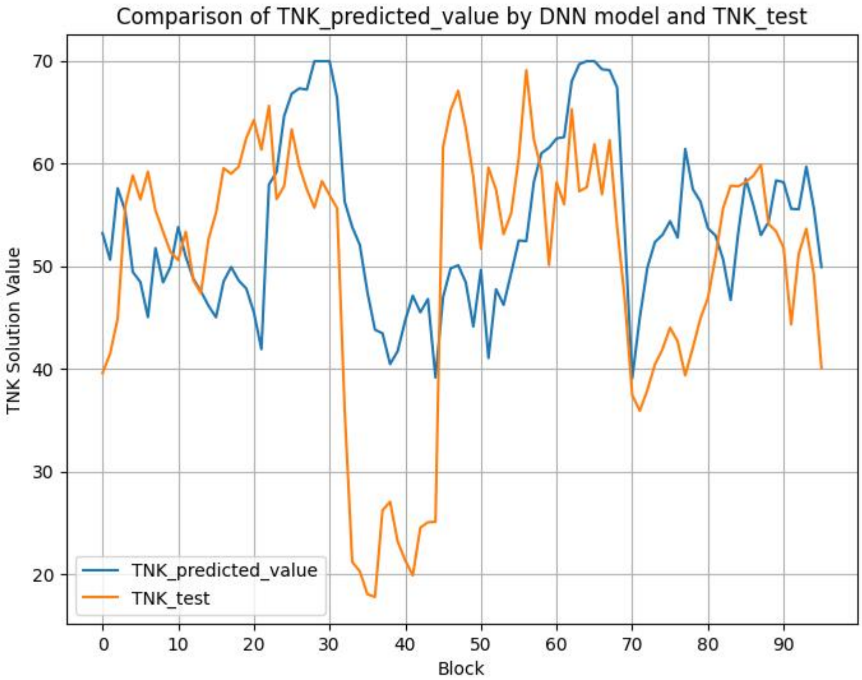

Figure 6.6: Tanakpur Import Solution by DNN model and test

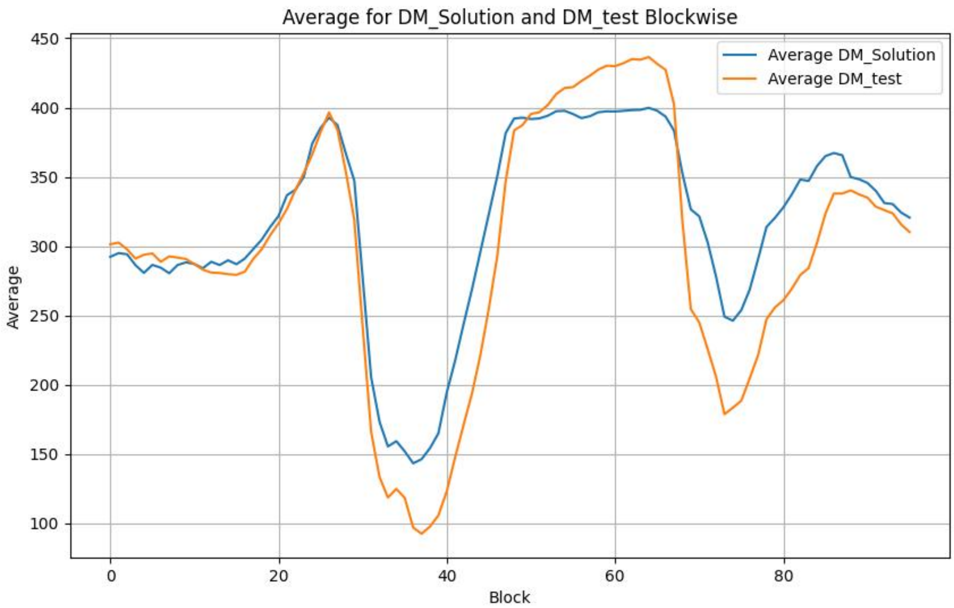

Figure 6.7: Average Dhalkebar-Muzzaffarpur solution vs actual blockwise

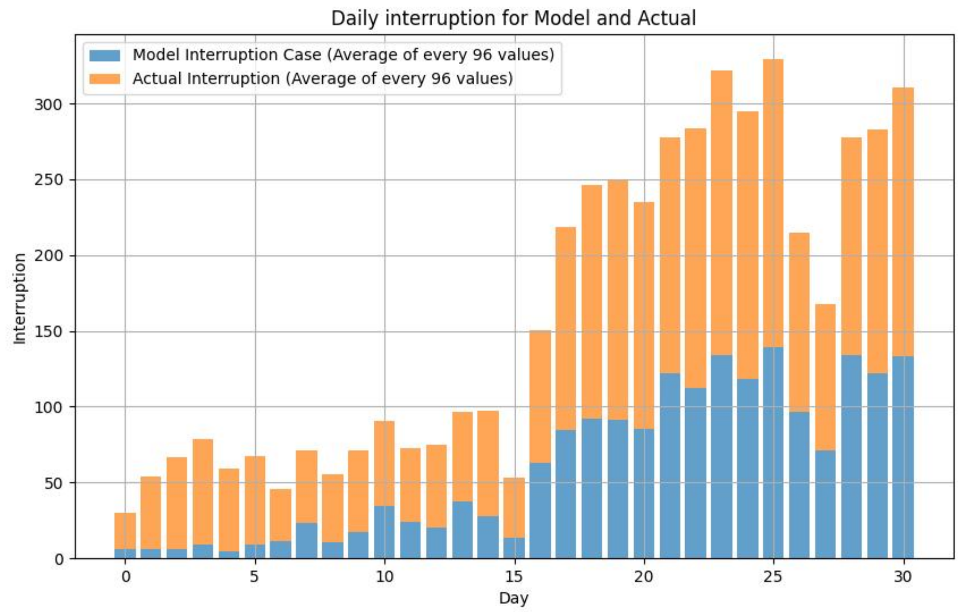

Figure 6.8: Interruption Actual Vs Predicted

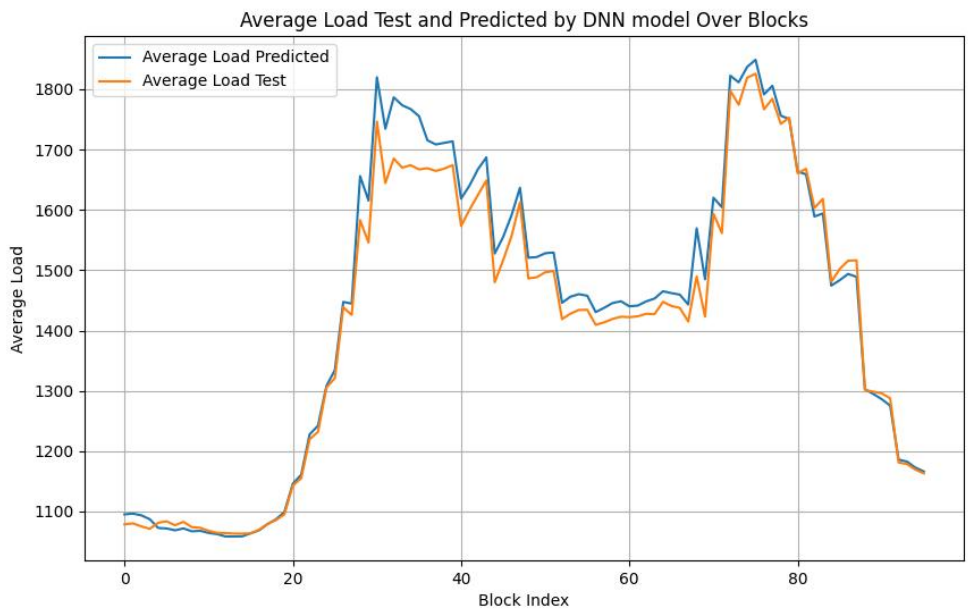

Figure 6.9: Average Load Predicted By DNN model Vs Test

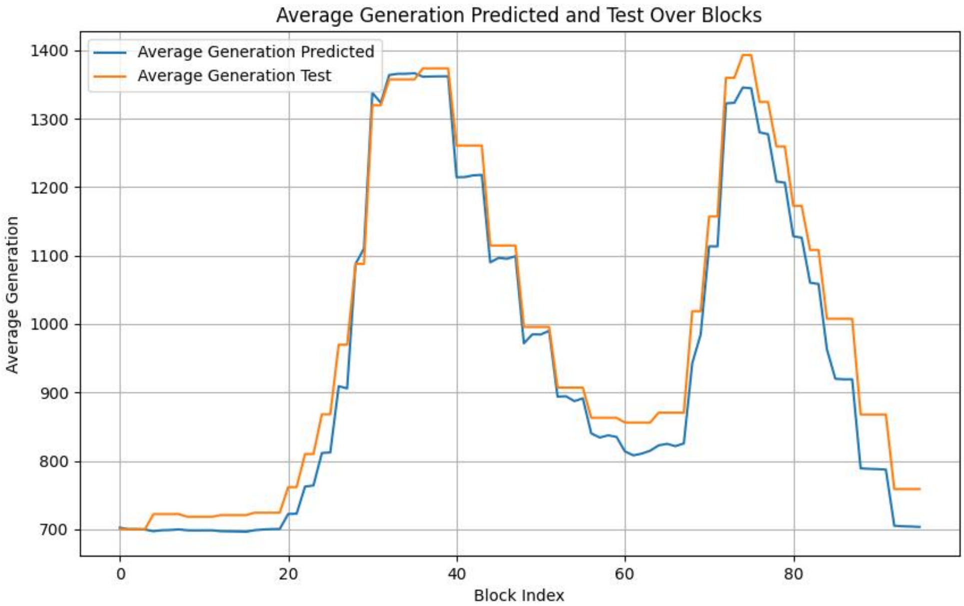

Figure 6.10: Average Generation blockwise predicted by DNN Vs test

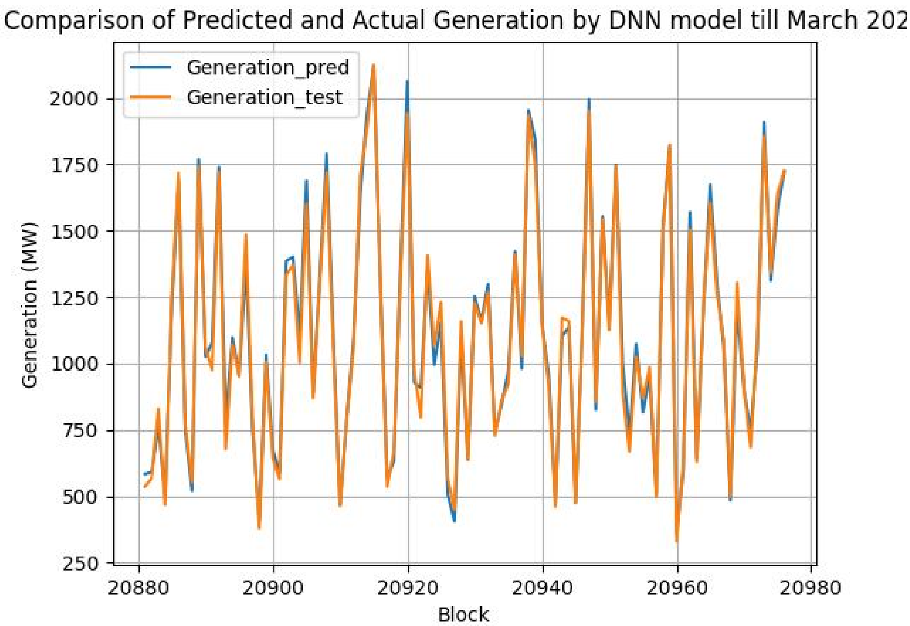

Figure 6.11: Generation Actual and Predicted by DNN

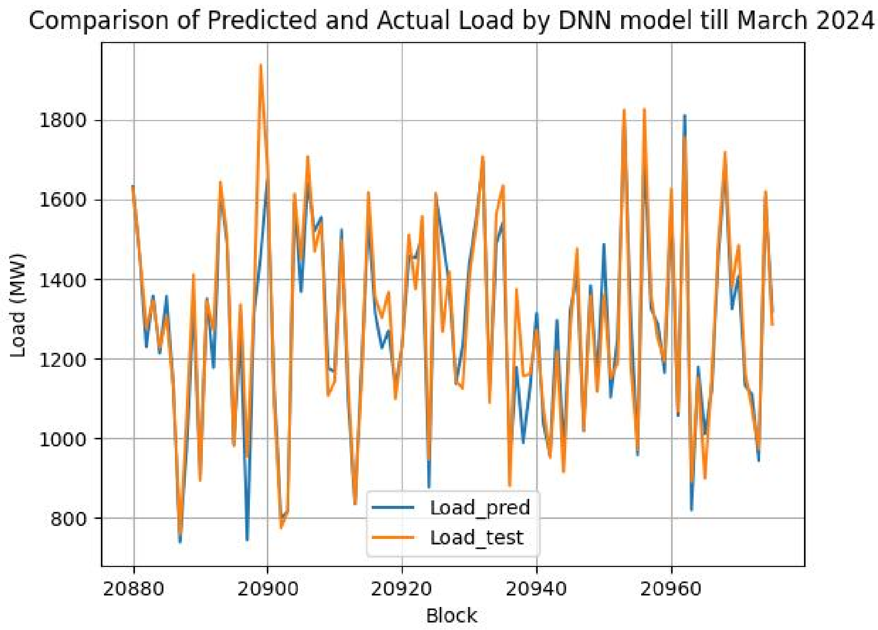

Figure 6.12: Load Actual and Predicted by DNN

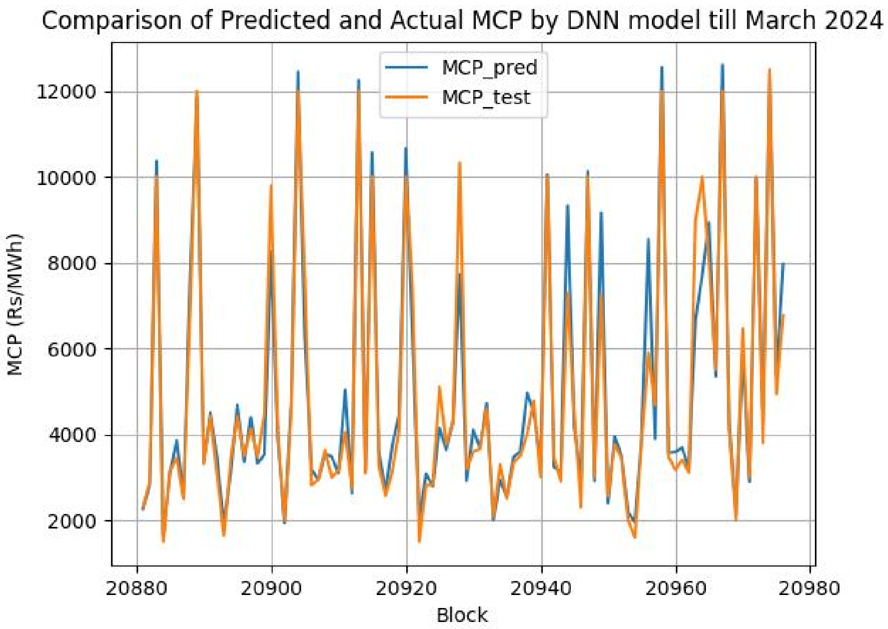

Figure 6.13: MCP Actual and Predicted by DNN till March 2024

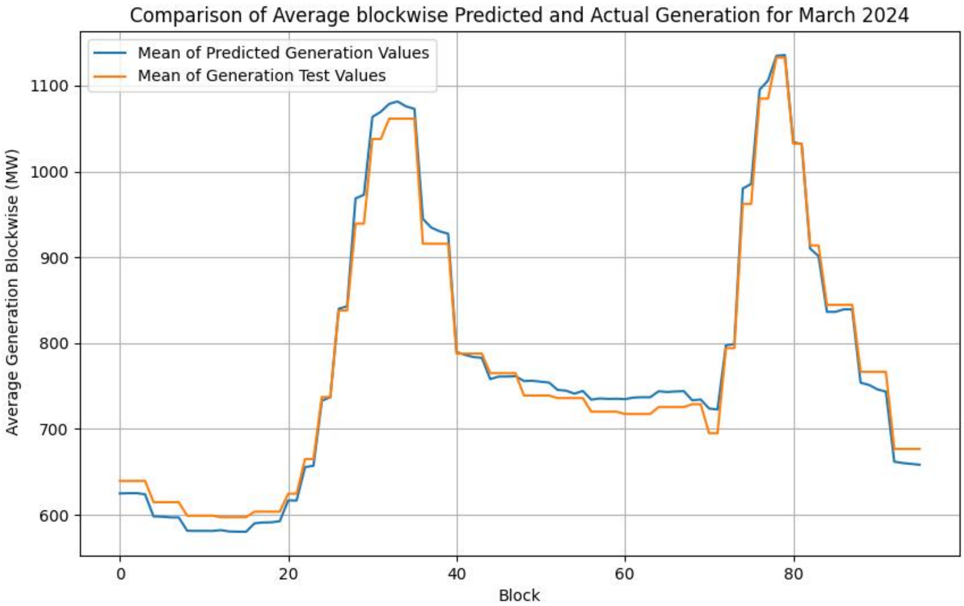

Figure 6.14: Blockwise Average Generation Actual MW Import Predicted by DNN till March 2024

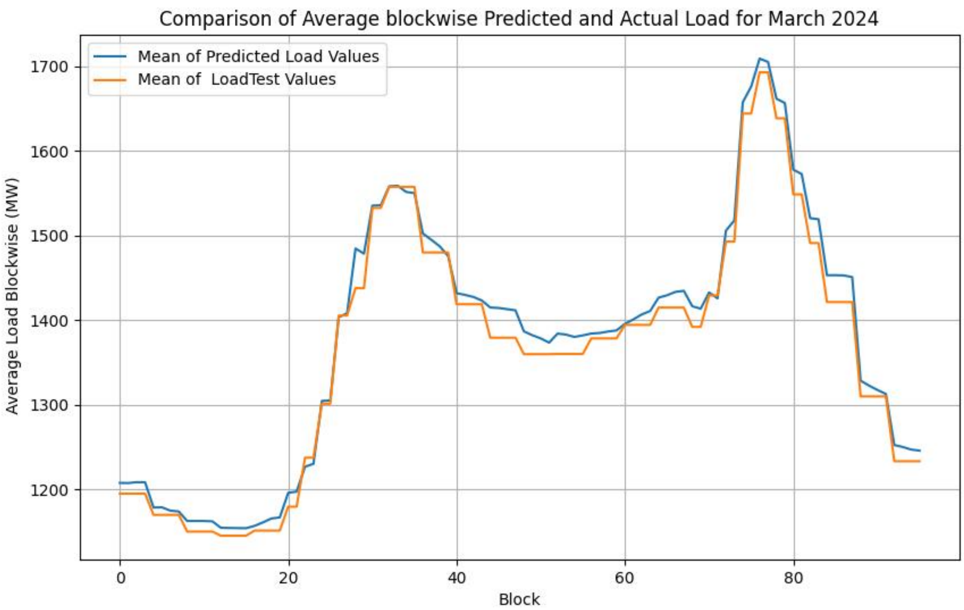

Figure 6.15: Blockwise Average Load Actual and Predicted by DNN till March 2024

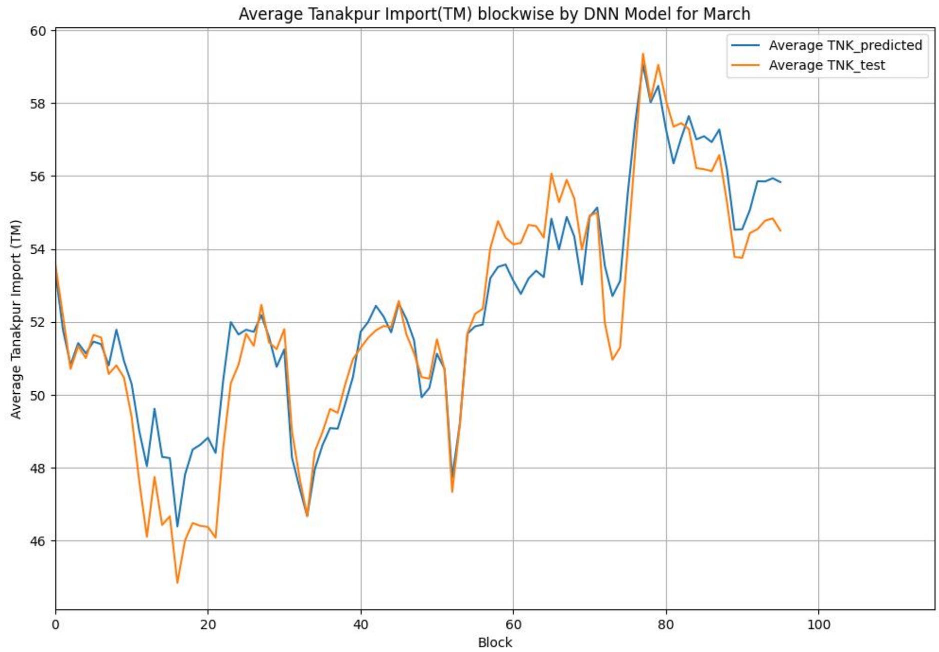

Figure 6.16: Blockwise Average Tanakpur Import Actual and Predicted by DNN till March 2024

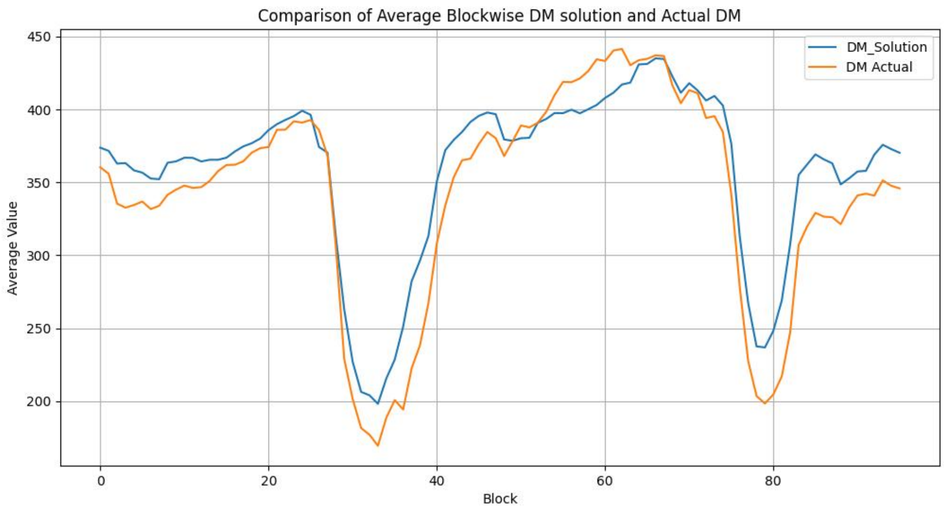

Figure 6.17: Blockwise Average DM Import Actual and Predicted by DNN for March 2024

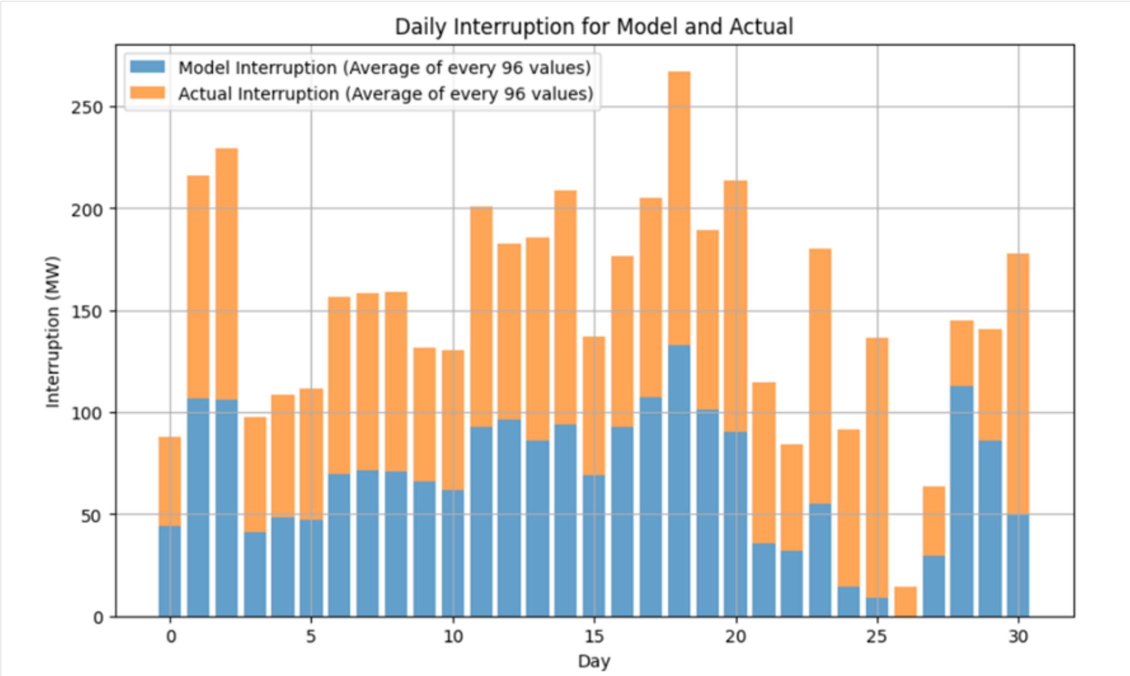

Figure 6.18: Interruption Actual Vs. Predicted for March 2024

We also aimed to evaluate the model's performance for March 2024. Fig. 6.11 through Fig. 6.17 demonstrate the DNN model's strong capability in efficiently forecasting load, generation, MCP, and import values for both DM and TM. Fig. 6.11 to Fig. 6.13 shows the comparison of predicted and actual values of generation,load and MCP when datas were taken till March 2024. Fig. 6.14 to Fig. 6.17 shows the blockwise average value of generation, load, TM import and DM import predicted by DNN model compared with the actual values. The plots show that the model serves as an effective forecasting metric for DAM, demonstrating its reliability. From the Fig 6.18, it is evident that the daily interruptions can be reduced using the DNN model for March 2024. This demonstrates how the DNN model serves as an effective tool not only for reliably forecasting load generation but also for minimizing interruptions.

We sourced actual and scheduled import data from Dhalkebar-Muzzafarpur and Mahendranagar-Tanakpur, 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 were provided in a 15-minute time format, which is crucial for accurate forecasting as it adheres to the requirements of the bidding format.

6.2.2 RTM Bidding with LSTM Model

Day-ahead load forecasting and bidding play a crucial role in ensuring grid stability by anticipating demand, while RTM trading offers the flexibility to adapt to sudden changes in supply and demand. In our approach, we not only employed a DNN model but also utilized Long Short-Term Memory (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 Dhalkebar-Muzzafarpur and Mahendranagar-Tanakpur, the LSTM model forecasted the import values required for bidding in the RTM. This approach ensured that our bidding strategy was closely aligned with RTM dynamics, thereby bolstering our capacity to make timely and well-informed decisions.

Table 6.3: 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
Application	Real-time market bidding

Following data preprocessing and normalization using the Pandas library, we created a PyTorch Dataset class to manage the time series data, dividing it into training and testing sets. We divided the dataset into testing and training subsets, with the training set consisting of 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, which allowed 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 will be used, providing a short-term forecasting horizon. Our LSTM model, featuring an LSTM layer with 64 hidden units and 2 layers, followed by a fully connected layer, was trained over 3 epochs using Mean Squared Error

(MSE) loss and optimized with the Adam optimizer. The accuracy of LSTM model computed using the coefficient of determination, R^2 score is as shown in Table 6.4.

Table 6.4: LSTM Model Accuracy

Parameter	Description
Model Accuracy (DM import)	98.9%
Model Accuracy (TNK import)	98.62%
Model Accuracy (Rtm MCP)	92.06%
Test Loss	0.0002

Fig. 6.19 till Fig. 6.24 shows the capability of LSTM to maintain shortterm forecasting efficiency where Fig. 6.19 to Fig. 6.21 shows the value of DM import, TM import and MCP as predicted by LSTM model for RTM bid till January 2024 where as Fig. 6.22 to Fig. 6.24 shows the same values when the simualtion was run till March 2024. Both of the cases demonstrates excellent performance of the model.

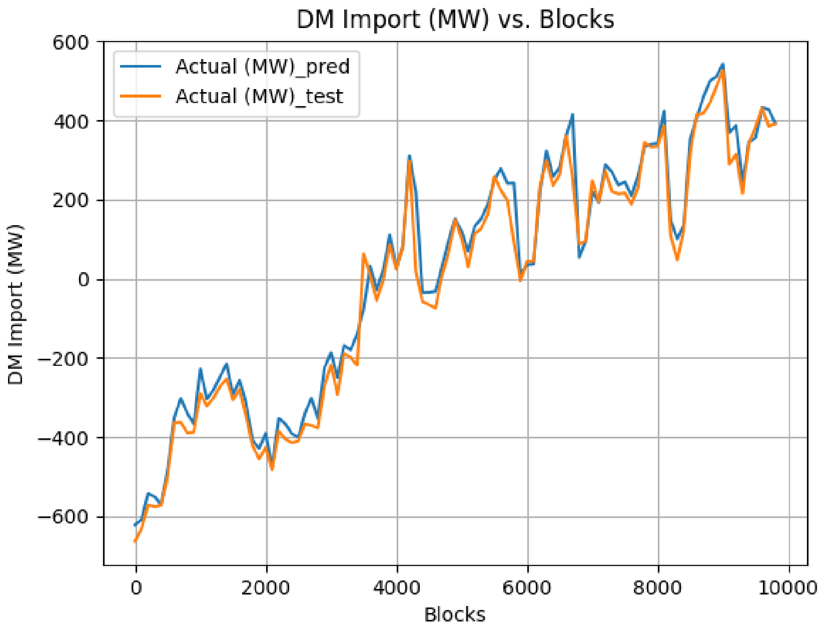

Figure 6.19: Dhalke-Muzzafarpur Actual Import Predicted by LSTM

6.3 Concluding Remarks

Using the RTM model allows us to bid closer to real time and if bidded in RTM for both buy/sale, the DSM charge can be reduced. Using the Central Electricity Regulatory Commission (CERC)'s rule we have devised a function in Python programming which will be used for the calculation of DSM charge which we call DSM

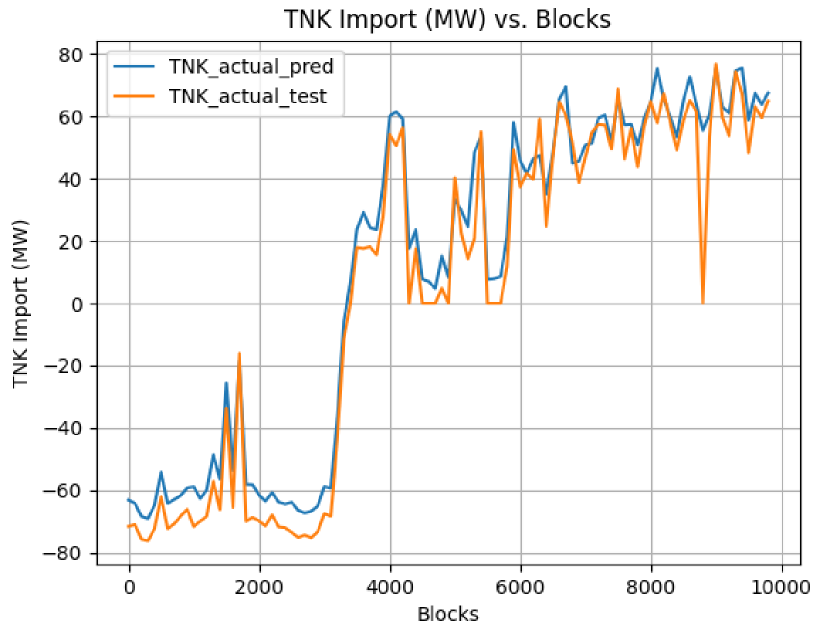

Figure 6.20: Tanakpur-Mahendranagar Actual Import Predicted by LSTM

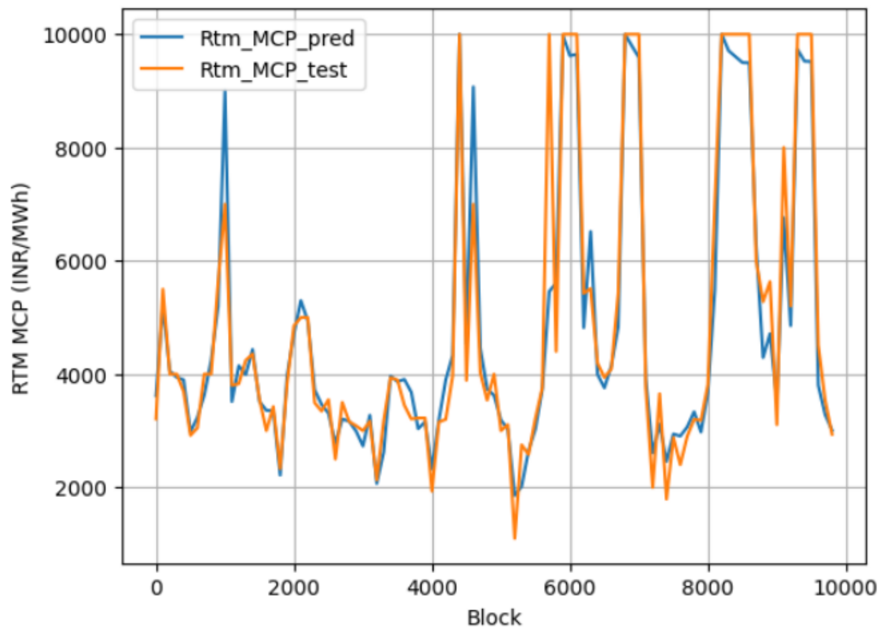

Figure 6.21: MCP Actual and Predicted by LSTM

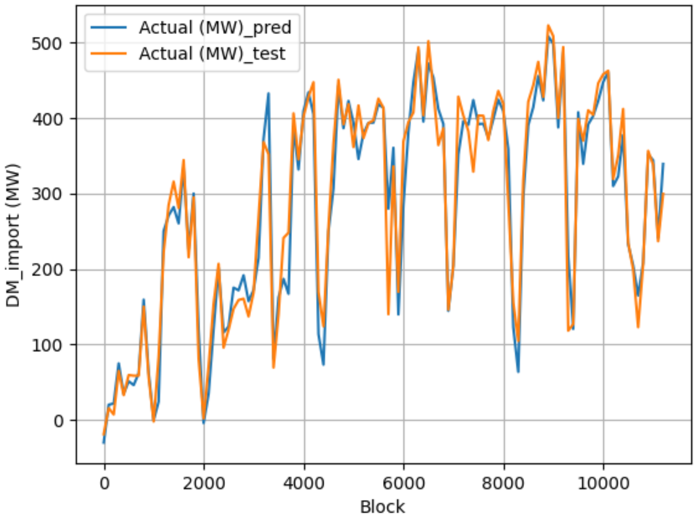

Figure 6.22: Dhalke-Muzzafarpur Actual Import Predicted by LSTM for March 2024

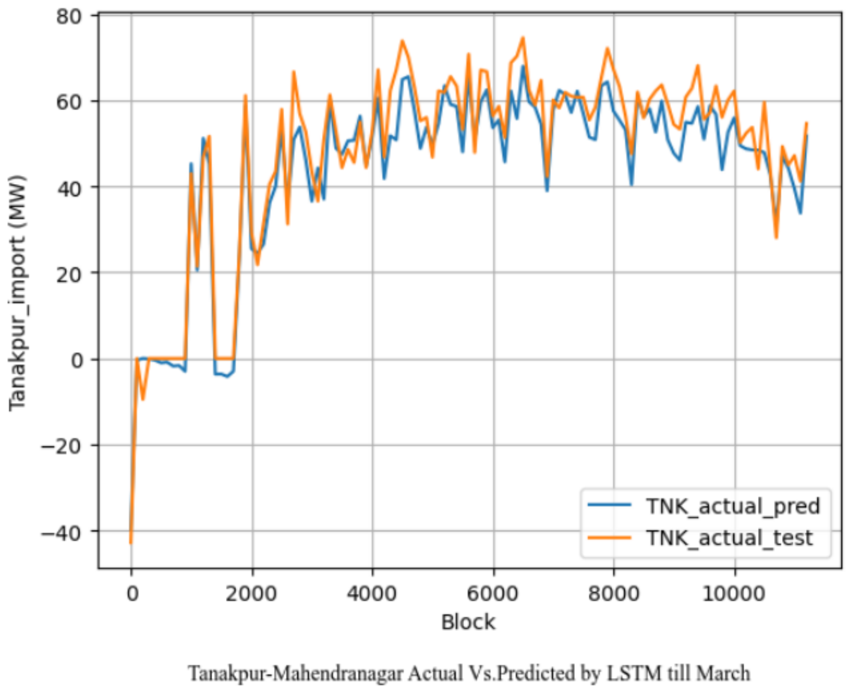

Figure 6.23: Tanakpur-Mahendranagar Actual MW Import Predicted by LSTM for March 2024

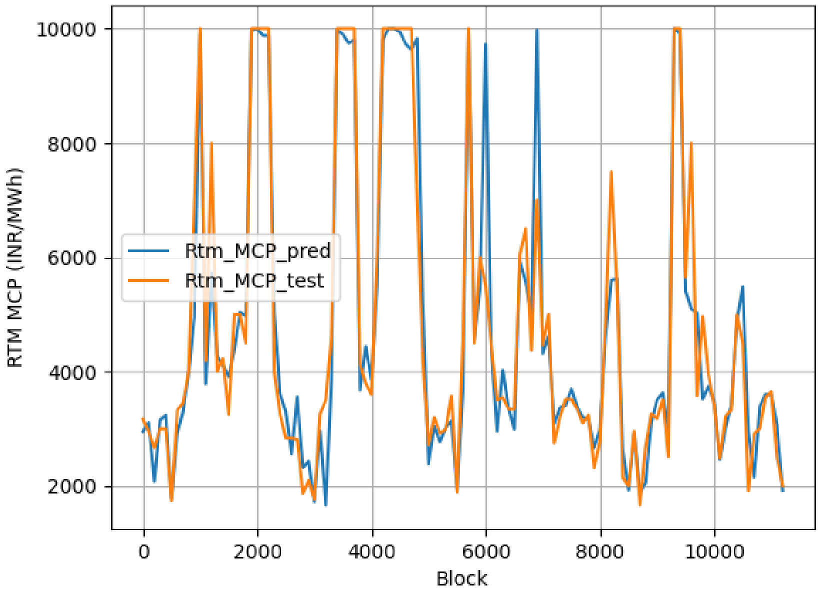

Figure 6.24: MCP Predicted by LSTM for March 2024

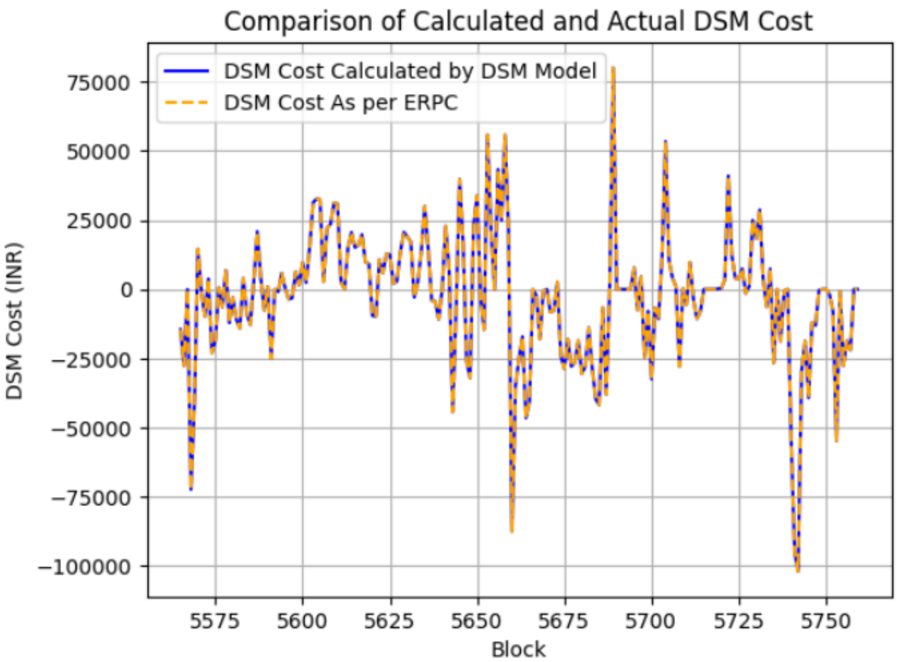

Figure 6.25: Comparison of DSM function with Actual

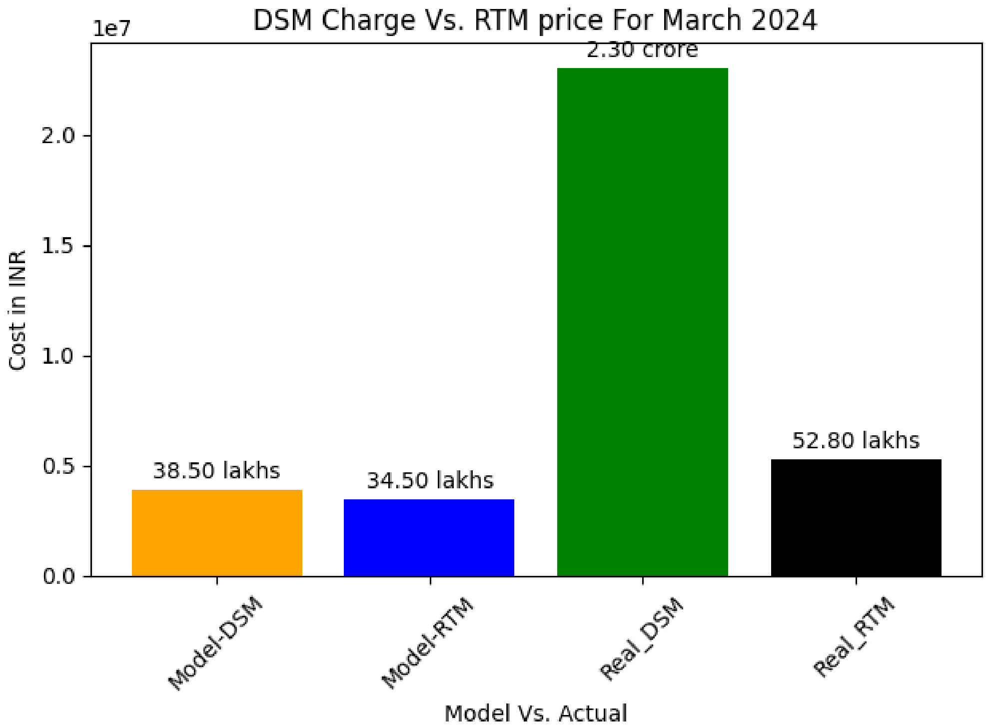

Figure 6.26: Actual Vs. Model DSM Comparison for March 2024

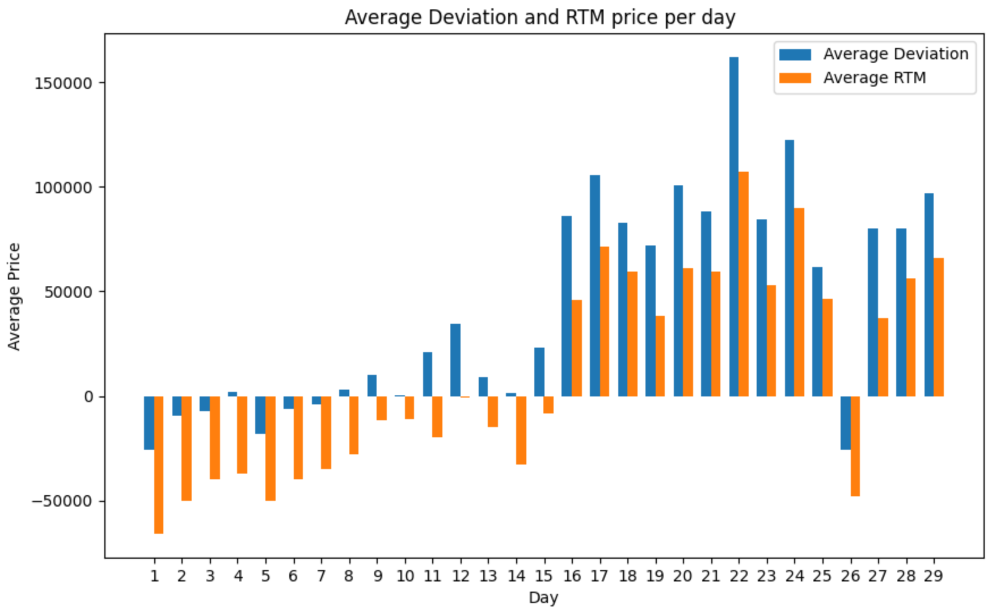

Figure 6.27: DSM Charge Vs RTM Price

function. To evaluate the effectiveness of the function developed in accordance with CERC guidelines, we conducted a comparative analysis of DSM costs derived from the model against those updated on the website. The results, depicted in Fig. 6.25, underscore the remarkable performance of our model with 99.99% efficiency. This DSM model was then used to calculate the scenario that if instead of trading in RTM market the energy was taken or supplied to deviation pool and Fig.6.26 showed that the proposed algorithm achieved significant cost saving compared to actual scenario (up to 85%). It is further evident from the Fig. 6.27 that higher cost has to be paid in deviation pool when importing but lower cost when exporting to deviation pool rather than trading in RTM. So, RTM proves to be beneficial from cost saving point of view as well.

CHAPTER SEVEN: CONCLUSION & FUTURE WORKS

This thesis primarily focuses on regression analysis and time series prediction. For DAM, it employed a fully connected deep neural network to forecast load, plan generation, and provide DAM bids as solution consider several factors. Additionally, an LSTM model was utilized for RTM bidding. We present a novel algorithm that provides an informed bidding decisions for both DAM and RTM using these models that considers several real constraints. Throughout the forecasting process, various influencing factors and challenges were encountered, which will be comprehensively discussed in this chapter along with the future works.

7.1 Factors affecting Load

Meteorological Factors

Changes in load patterns are largely influenced by meteorological factors, particularly for utilities with significant weather-sensitive loads such as heating, air conditioning, and agricultural irrigation [35]. Load levels fluctuate in response to climatic conditions. Temperature, cloud, rainfall, wind, precipitation are key meteorological factors considered in load forecasting due to their impact on system load .

Time Factors

Load is influenced by the time of the day, holiday, festivals and seasons.

Economic Aspects

Economic landscape in which the utility operates greatly impacts electricity consumption profile. While these economic factors are not considered in Short-Term Load Forecasting, they should be accounted for in longer-term forecasting models.

Random Factors

Random disturbances in some feeder, fault in some major transmission line, partial system collapse, unplanned holidays can cause unplanned variation in the load.

7.2 Challenges in developing accurate model for Forecasting

Quality of Data

Machine learning relies on data to generate predictions, making it a fundamental component of the model. AI algorithms learn from the input received, adjusting their parameters to minimize errors and improve accuracy. However, if the training data contains numerous errors, the algorithms will incorporate these errors into their learning process, leading to inaccurate predictions. Therefore, it is essential to provide high-quality data to ensure reliable predictions. Additionally, the dataset must be sufficient to enable the recognition of patterns and facilitate accurate predictions.

Interruption Data

Interruption is taken as the load that could not be supplied either due to low schedule or due to some constraints. However, computed total load data is inaccurate due to the lack of precise interruption data. This absence of actual data on power cuts, restrictions undermines the reliability of load data. These issues can significantly affect forecasting model posing challenges in validating model parameters.

Generation

Majority of generating sources in Nepal are Run of River (ROR) type . KaliGandaki A hydropower plant (KGA) is six hours peaking , Marsyangdi HPP is 4 hours daily peaking ROR, Chameliya HPP is daily 6 hours peaking, Middle Marsyangdhi hpp is daily 5 hours peaking, Upper Tamakoshi is 4hrs daily peaking. During times of low demand, the load follows its typical patterns, behaving naturally. However, during peak hours, manual load management measures are implemented, which suppress load behavior. Also, during peak periods, load behavior is predominantly influenced by the availability of generation resources. Relying on generation resources presents a notable challenge in the development of load forecasting models.

Load Data

The load data in our case was collected from various sources. Some of them were taken from SCADA while some were data manually entered by operators. Some of them were 15 mins data while some were hourly data converted to 15 mins. Poor data quality within the dataset may stem from inaccuracies in measurement, issues with data transmission, communication, and human mistakes. Accurate forecasting requires accurate and reliable data. Furthermore, the load data is not categorized by region or type (industrial, commercial, irrigation, domestic), making it challenging to classify load patterns as weather, season or holiday-dependent.

7.3 Conclusion

In this research a Deep Neural Network was developed that helps in prediction of load, generation and the import from India through Dhalkebar-Muzzaffarpur and Tanakpur-Mahendranagar transmission lines which aids in bidding for the DAM. Additionally, an LSTM model was used to predict the import and RTM MCP which will be used for RTM bidding. Also, a DSM model which is based on CERC guidelines was devised for the calculation of DSM charges. 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. It emphasizes the significance of accurate forecasting for aligning bids closely with real conditions in the DAM and underscores the pivotal role of RTM trading in managing unforeseen circumstances and minimizing deviations. The DSM charge which we had to pay/receive for deviation and the price at which we trade in the RTM market was studied and it was found that the DSM charge could be reduced significantly by the participation of Nepal in the RTM market using the $HeADR$ algorithm presented in this thesis as it allows bidding closer to real time with greater accuracy in forecasting and checking for the real constraints that affect the import and export level through these DM and TM interfaces. This study highlights that Nepal's participation in the RTM market in IEX alongside DAM will be beneficial for Nepal and helps in minimizing the deviation charge significantly with up to 85% cost saving, provided timely and effective execution of the proposed methodology.

7.4 Future Direction

- Classify load into categories such as domestic, industrial, weather-dependent, weather-independent, irrigation, and domestic load.

- Segment the load geographically into eastern and western regions and conduct a comprehensive load flow analysis. Include regional generation data and consider additional system constraints for accurate modeling.

- Analyze the impact of political and other external factors on bidding and bid clearing processes by integrating probabilities related to the influence of external factors in future analyses.

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APPENDIX A: DATA SAMPLE

Date	temp	rain	rel_hum	cld	wnd	day	sunshine	Taplejung_river_ discharge (mÂ^3/s)	CHM_river_ discharge (mÂ^3/s)	UTK_river_ discharge (mÂ^3/s)	KGA_discharge	lamjung-discharge
3/5/2021 23:45	16.33	0	60.29	2.09	8.03	0	0	14.7	26.1	24.35	1.88	30.33
3/6/2021 0:00	15.86	0	77.38	12.34	5.16	0	0	14.92	26.1	24.53	1.9	31.73
3/6/2021 0:15	15.86	0	77.38	12.34	5.16	0	0	14.92	26.1	24.53	1.9	31.73
3/6/2021 0:30	15.86	0	77.38	12.34	5.16	0	0	14.92	26.1	24.53	1.9	31.73
3/6/2021 0:45	15.86	0	77.38	12.34	5.16	0	0	14.92	26.1	24.53	1.9	31.73
3/6/2021 1:00	15.27	0	63.09	4.09	7.87	0	0	14.92	26.1	24.53	1.9	31.73
3/6/2021 1:15	15.27	0	63.09	4.09	7.87	0	0	14.92	26.1	24.53	1.9	31.73
3/6/2021 1:30	15.27	0	63.09	4.09	7.87	0	0	14.92	26.1	24.53	1.9	31.73
3/6/2021 1:45	15.27	0	63.09	4.09	7.87	0	0	14.92	26.1	24.53	1.9	31.73
3/6/2021 2:00	14.57	0	65.88	4.79	8.44	0	0	14.92	26.1	24.53	1.9	31.73
3/6/2021 2:15	14.57	0	65.88	4.79	8.44	0	0	14.92	26.1	24.53	1.9	31.73
3/6/2021 2:30	14.57	0	65.88	4.79	8.44	0	0	14.92	26.1	24.53	1.9	31.73
3/6/2021 2:45	14.57	0	65.88	4.79	8.44	0	0	14.92	26.1	24.53	1.9	31.73
3/6/2021 3:00	14.33	0	66.71	5.29	8	0	0	14.92	26.1	24.53	1.9	31.73
3/6/2021 3:15	14.33	0	66.71	5.29	8	0	0	14.92	26.1	24.53	1.9	31.73
3/6/2021 3:30	14.33	0	66.71	5.29	8	0	0	14.92	26.1	24.53	1.9	31.73
3/6/2021 3:45	14.33	0	66.71	5.29	8	0	0	14.92	26.1	24.53	1.9	31.73
3/6/2021 4:00	14.19	0	67.84	4.54	7.7	0	0	14.92	26.1	24.53	1.9	31.73
3/6/2021 4:15	14.19	0	67.84	4.54	7.7	0	0	14.92	26.1	24.53	1.9	31.73

Figure A.1: Weather Data Sample

[Source:Open-Meteo]

Date	IsHoliday	Prev_day _gen	Prev_day _load	Prev_day-import	Prev_day _DM	Prev_day _TNK	TNK	Avg_7_T NK	DM	Avg_7_D M	Generati on	Avg_7_ Gen	Load	Avg_7 _Load	Import	Avg_7_I mport	Interrupti on
1/4/2023 23:45	0	653	1016.05	82	211.2	69.85	71.57	58.74143	276.07	220.3443	626	649.29	1054.6	1008	81	80	0
1/5/2023 0:00	0	633	1009.05	81	220.8	74.25	69.51	58.63143	279.56	218.5157	596	621.57	1028.1	979.3	83	80.57143	0
1/5/2023 0:15	0	633	1007.23	81	218.47	74.76	69.58	59.16286	276.65	207.9557	596	621.57	1025.2	969.3	83	80.57143	0
1/5/2023 0:30	0	633	980.42	81	192.29	74.13	67.42	62.81429	248.73	205.2557	596	621.57	995.15	970.2	83	80.57143	0
1/5/2023 0:45	0	633	967.79	81	182.69	71.1	68.66	59.02143	251.64	196.6129	596	621.57	999.3	957.8	83	80.57143	0
1/5/2023 1:00	0	639	966.41	81	185.6	60.81	69.48	58.84571	234.47	191.8329	596	591.71	980.95	917.8	81	75.42857	0
1/5/2023 1:15	0	639	971.77	81	187.93	63.84	64.74	57.13571	244.36	193.9543	596	591.71	986.1	918.2	81	75.42857	0
1/5/2023 1:30	0	639	978.27	81	193.75	64.52	65.51	55.50857	234.47	196.5314	596	591.71	976.98	919.2	81	75.42857	0
1/5/2023 1:45	0	639	977.32	81	195.49	61.83	69.08	56.62571	235.93	196.4043	596	591.71	982.01	920.2	81	75.42857	0
1/5/2023 2:00	0	675	1009.2	83	189.38	61.82	69.9	56.71286	224.87	190.0057	525	598	897.77	914.7	78	70	0
1/5/2023 2:15	0	675	1011.44	83	184.73	68.71	69.12	58.69571	229.24	189.2986	525	598	901.36	916	78	70	0
1/5/2023 2:30	0	675	1021.72	83	200.44	63.28	65.11	58.92714	233.31	190.5043	525	598	901.42	917.4	78	70	0
1/5/2023 2:45	0	675	1010.59	83	187.93	64.66	63.26	58.55	227.49	193.3714	525	598	893.75	919.9	78	70	0
1/5/2023 3:00	0	580	927.58	78	202.18	67.4	63.24	57.41143	234.18	191.8329	525	579.71	900.42	890.7	78	61.71429	0
1/5/2023 3:15	0	580	907.12	78	181.24	67.88	57.67	61.02714	234.47	194.4129	525	579.71	895.14	896.9	78	61.71429	0
1/5/2023 3:30	0	580	919.35	78	192.87	68.48	54.33	60.17857	242.04	193.62	525	579.71	899.37	895.2	78	61.71429	0
1/5/2023 3:45	0	580	896.07	78	175.71	62.36	61.02	58.23143	237.67	195.45	525	579.71	901.69	895.1	78	61.71429	0
1/5/2023 4:00	0	610	917.8	78	187.05	42.75	61.7	55.41857	235.05	194.5743	525	595.43	899.75	912.7	78	67.28571	0
1/5/2023 4:15	0	610	937.06	78	188.51	60.55	64.39	60.54	239.71	199.4814	525	595.43	907.1	922.7	78	67.28571	0

Figure A.2: Load Generation Data Sample

[Source: load Dispatch Center (LDC) logsheet]

Date	Dhalke	Dhalke_Mirchaya_1	Dhalke_Mirchaya_2	Dhalke-Khimti_2	Dhalke-Khimti_1	Dhalke-Nawal-1	Dhalke-Nawal-2	Het-Kamane
7/30/2023 23:45	-92.8839	-45.62299612	-45.69950152	290.019043	290.214386	-18.29	-18.04	-90.69
7/31/2023 0:00	-93.2369	-42.88874348	-42.97117744	290.019043	290.214386	-29.03	-28.53	-93.63
7/31/2023 0:15	-93.0789	-40.23764376	-40.31225084	290.019043	290.214386	-34.37	-33.9	-97.45
7/31/2023 0:30	-91.8443	-39.46405984	-39.53198656	290.019043	290.214386	-37.86	-37.31	-95.07
7/31/2023 0:45	-92.5633	-37.27537636	-37.30931152	287.1515988	287.461163	-33.61	-33.15	-92.57
7/31/2023 1:00	-92.3679	-35.94132356	-35.98877976	292.7674465	292.2145368	-0.17	0.03	-91.04
7/31/2023 1:15	-92.3489	-36.97552652	-37.01777756	292.7352295	292.3538513	11.92	11.9	-93.54
7/31/2023 1:30	-89.984	-36.82178536	-36.85838168	292.7352295	292.3538513	9.92	9.96	-90.16
7/31/2023 1:45	-88.6308	-35.84956908	-35.88386348	292.7352295	292.3538513	1.75	1.92	-93.82
7/31/2023 2:00	-90.4831	-34.79450896	-34.84659544	292.7352295	292.3538513	3.88	4.04	-90.88
7/31/2023 2:15	-90.2887	-35.91672112	-35.94867264	292.7352295	292.3538513	-14.2	-13.9	-90.38
7/31/2023 2:30	-91.5524	-34.85757016	-34.9065178	292.7352295	292.3538513	-5.97	-5.7	-88.68
7/31/2023 2:45	-91.0409	-32.44314812	-32.4612386	292.7352295	292.3538513	-6.84	-6.6	-88.67
7/31/2023 3:00	-90.9438	-35.12063312	-35.14652388	292.7352295	292.3538513	-1.45	-1.33	-92.86
7/31/2023 3:15	-91.0025	-30.41928836	-30.44189376	292.7352295	292.3538513	-3.74	-3.6	-88.09
7/31/2023 3:30	-90.6466	-31.40086392	-31.40408404	292.7352295	292.3538513	-9.22	-8.98	-88.85
7/31/2023 3:45	-90.4495	-32.93207496	-32.95267236	292.7352295	292.3538513	-4.57	-4.33	-87.69
7/31/2023 4:00	-89.1984	-32.42160876	-32.43217148	292.7352295	292.3538513	-2.5	-2.31	-89.04
7/31/2023 4:15	-86.9616	-32.87384212	-32.92019796	292.7352295	292.3538513	-0.72	-0.63	-92.72

Figure A.3: Line Loading Data Sample

[Source: SCADA]

Date	Time	Freq (Hz)	Actual (MWH)	Schedule (MWH)	Deviation (MWH)	Deviation (%)	DSM Payable (Rs.)	DSM Receivable (Rs.)	NCD (p/MWH)
1/15/2024	9:45	49.96	-46.618181	-13.05944	-33.558741	256.969219	397481.8	0	1000
1/15/2024	10:00	50.02	-45.454545	-15.320004	-30.134541	196.700608	355486	0	1000
1/15/2024	10:15	50.02	-44.654545	-18.053319	-26.601226	147.348119	311994.2	0	1000
1/15/2024	10:30	50.04	-38.036364	-18.979623	-19.056741	100.40632	142925.56	0	1000
1/15/2024	10:45	50.03	-30.254545	-24.842212	-5.412333	21.78684	55010.8	0	1000
1/15/2024	11:00	50.04	-50.981818	-47.392663	-3.589155	7.573229	26918.66	0	1000
1/15/2024	11:15	50.04	-69.090909	-62.537485	-6.553424	10.479193	49150.68	0	1000
1/15/2024	11:30	49.99	-84.218181	-81.279533	-2.938648	3.615483	24977.81	0	849.99
1/15/2024	11:45	50	-98.472726	-95.0301	-3.442626	3.622669	18983.18	0	551.42
1/15/2024	12:00	50.04	-98.836362	-95.0301	-3.806262	4.005323	14227.24	0	498.38
1/15/2024	12:15	50.02	-97.672726	-95.0301	-2.642626	2.78083	12072.72	0	456.85
1/15/2024	12:30	50	-95.490908	-95.0301	-0.460808	0.484907	2105.4	0	456.9
1/15/2024	12:45	49.98	-91.490908	-95.0301	3.539192	3.724285	0	13762.64	432.07
1/15/2024	13:00	50.02	-82.254545	-95.0301	12.775555	13.443693	0	38764.8	430.72
1/15/2024	13:15	50.03	-86.327272	-95.0301	8.702828	9.15797	0	29704.83	379.25
1/15/2024	13:30	50.03	-93.381817	-95.0301	1.648283	1.734485	0	5355.48	361.01
1/15/2024	13:45	49.98	-82.836363	-95.0301	12.193737	12.831447	0	31737.6	352.64
1/15/2024	14:00	49.99	-83.345453	-95.0301	11.684647	12.295733	0	31732.2	352.58
1/15/2024	14:15	50.03	-93.672726	-95.0301	1.357374	1.428362	0	4388.57	359.23
1/15/2024	14:30	49.99	-96.145454	-95.0301	-1.115354	1.173685	4185.98	0	375.29
1/15/2024	14:45	49.95	-90.763635	-95.0301	4.266465	4.489593	0	14720.06	383.35
1/15/2024	15:00	49.96	-90.763635	-95.0301	4.266465	4.489593	0	14976.95	390.04

Figure A.4: DSM Calculation Sample

[Source: Eastern Regional Power Committee (ERPC)]

Date	DM_MCP (INR/MWh)	Rtm_MCP (INR/MWh)
1/15/2024 0:15	3200.31	3182.62
1/15/2024 0:30	3170.74	3391.11
1/15/2024 0:45	3142.40	3470.94
1/15/2024 1:00	3110.24	3236.69
1/15/2024 1:15	2997.80	2800.19
1/15/2024 1:30	2950.94	2580.77
1/15/2024 1:45	2949.29	2606.19
1/15/2024 2:00	2949.16	2314.56
1/15/2024 2:15	2897.35	2593.15
1/15/2024 2:30	2800.33	2659.42
1/15/2024 2:45	2800.12	2650.15
1/15/2024 3:00	2757.99	2659.94
1/15/2024 3:15	2731.40	2659.77
1/15/2024 3:30	2711.44	2659.61
1/15/2024 3:45	2744.84	2679.21
1/15/2024 4:00	2714.12	2860.77
1/15/2024 4:15	2800.85	2700.61
1/15/2024 4:30	2846.46	2990.78
1/15/2024 4:45	2890.20	3182.92
1/15/2024 5:00	2899.64	3200.61
1/15/2024 5:15	3110.91	3534.24
1/15/2024 5:30	3186.21	3652.29

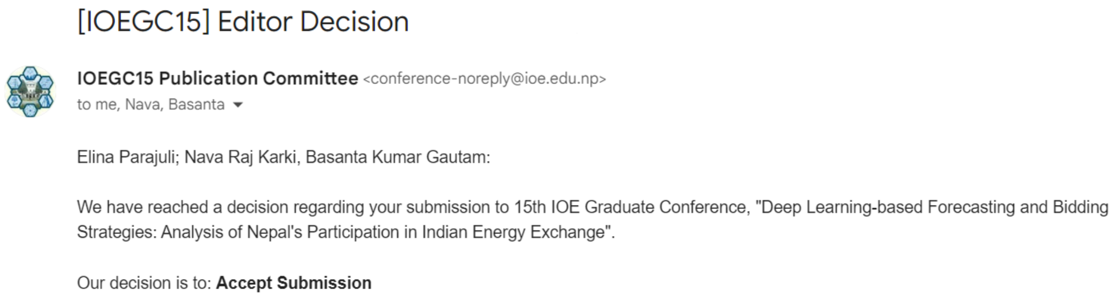
Figure A.5: IEX Data Sample

[Source: Indian Energy Exchange Limited (IEX)]

PUBLICATION

1. Elina Parajuli, Basanta Kumar Gautam and Nava Raj Karki, “Deep Learning-based Forecasting and Bidding Strategies: Analysis of Nepal’s Participation in Indian Energy Exchange,” in *15th IOE Graduate Conference, Pokhara, Nepal*, 2024

2. Elina Parajuli, Ashutosh Timilsina, Basanta Kumar Gautam and Nava Raj Karki, “Optimizing Electricity Market Bidding Strategies Through Deep Learning: Case Study of Nepal’s Energy Exchange Trends and Market Dynamics,” (Under Review)



[IOEGC15] Editor Decision

IOEGC15 Publication Committee <conference-noreply@ioe.edu.np>
to me, Nava, Basanta

Elina Parajuli; Nava Raj Karki, Basanta Kumar Gautam:

We have reached a decision regarding your submission to 15th IOE Graduate Conference, "Deep Learning-based Forecasting and Bidding Strategies: Analysis of Nepal's Participation in Indian Energy Exchange".

Our decision is to: **Accept Submission**

Figure A.6: IOEGC Paper Acceptance

IOE Graduate Conference
[Placeholder for Publication Information]

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 system modeling used. Section 3 discusses the experimental setup. Section 4 lists the results obtained and discusses them. Section 5 then 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.

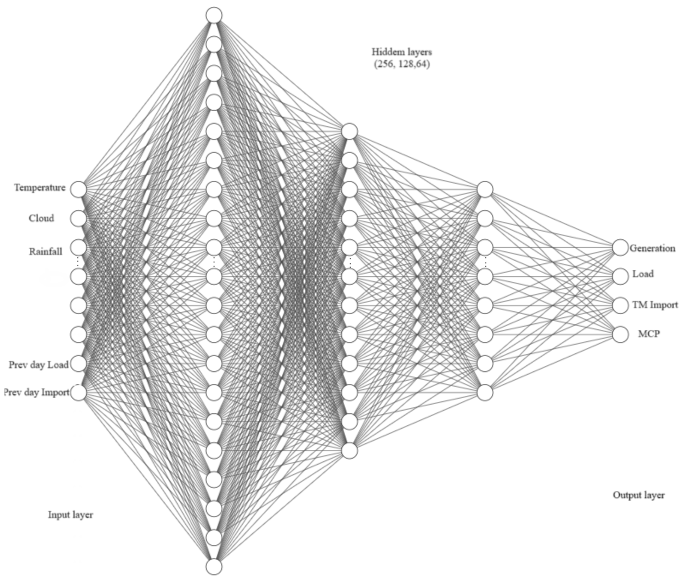

Figure 1: DNN Model architecture

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.

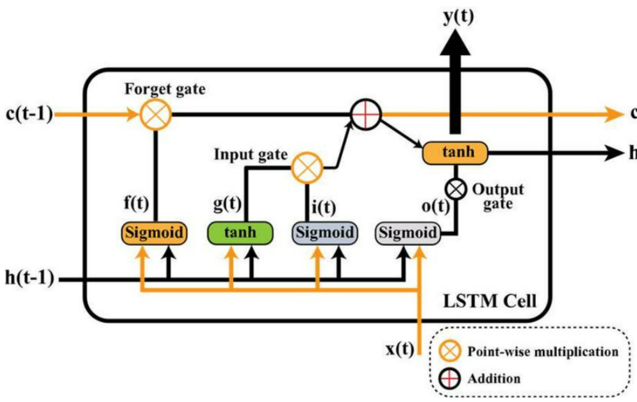

Figure 2: LSTM Model

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.

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,

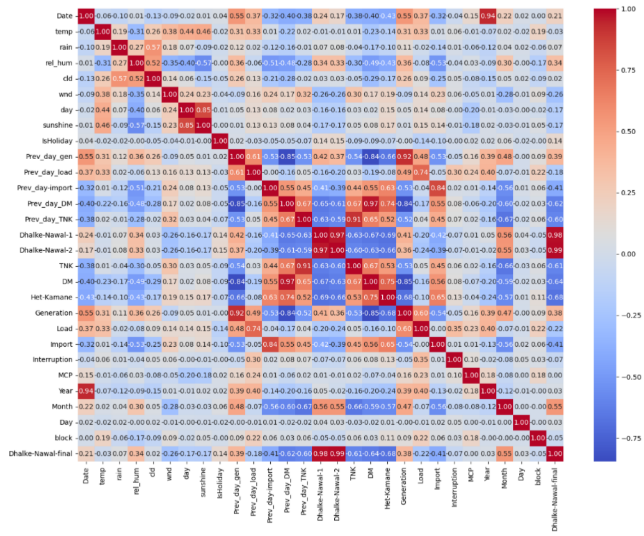

Figure 3: Correlation between target and features

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.

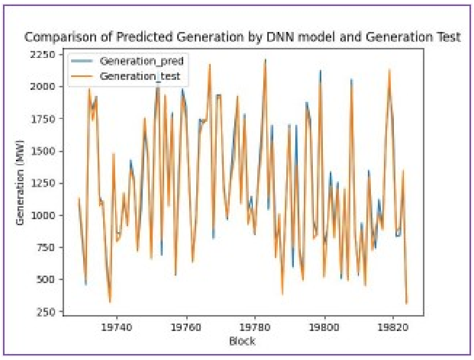

Figure 4: Generation Predicted by DNN value vs Test

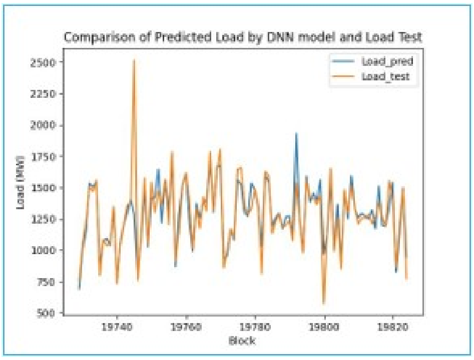

Figure 5: Load Predicted by DNN value vs Test

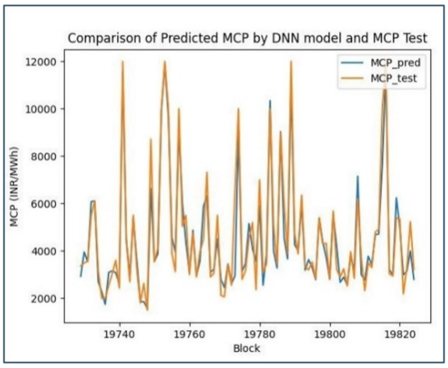

Figure 6: MCP predicted by DNN Model vs Test

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

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 3: DNN Model Accuracy

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

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.

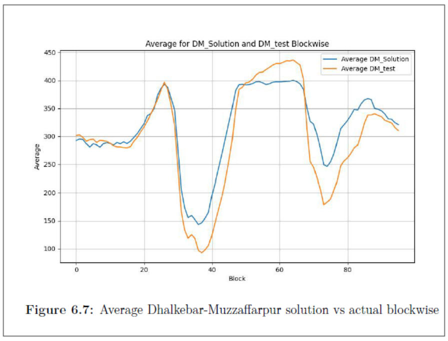

Figure 7: DM Import predicted by DNN model blockwise

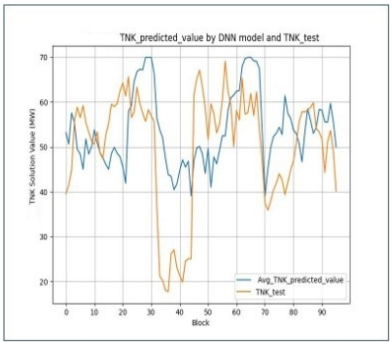

Figure 8: Tanakpur predicted by DNN model blockwise

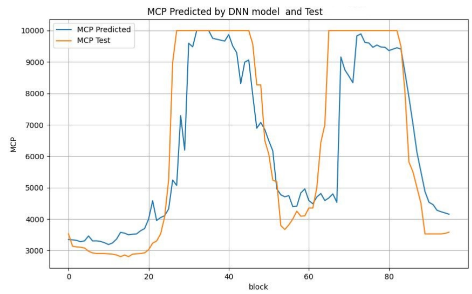

Figure 9: MCP predicted by DNN Model as per blocks

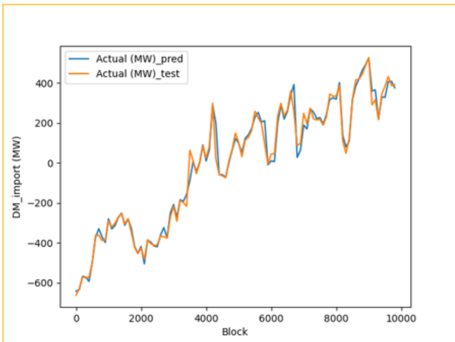

Figure 10: Actual Vs predicted DM Import by LSTM Model

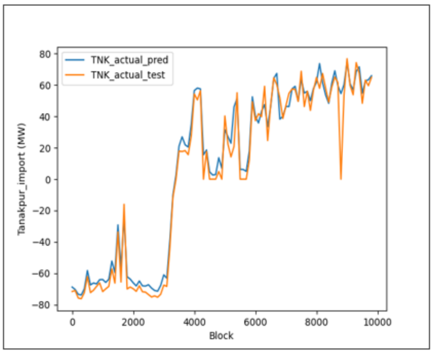

Figure 11: TNK Actual MW Import Predicted by LSTM

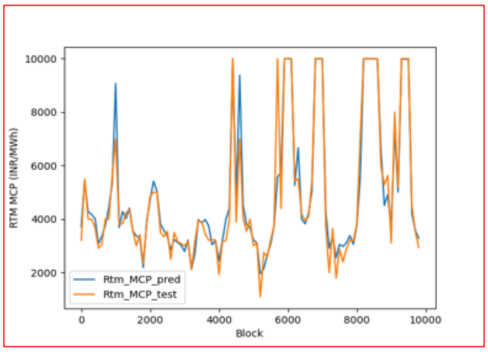

Figure 12: Real time MCP Predicted by LSTM

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.

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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