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Optimization Of Electric Vehicle Charging Infrastructure Using LSTM AND GNN (Case study of Nepal)

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Abstract
The advancement of EV technology is accelerating over the world. For Nepal, there is a good opportunity to reduce its oil use, which will help to reduce the trade imbalance. The Nepalese government has also established a number of regulatory measures and national policies to address the country's developing trend of electric vehicle (EV) adoption. Current trends suggest that electric vehicles (EVs) are a promising technology for road network mobility. The dearth of easily accessible charging facilities will be a detriment to EV adoption. As a result, charging station placement and charging activity scheduling have gained traction among scholars all around the world. In the literature, various planning and scheduling models have been developed. Each model is distinct and has its own characteristics. Furthermore, the performance of the models varies and is region dependent. A model that works well in a developing country may not work well in a developed country, and vice versa. This article will present an optimization of charging station placement recommendations, charging demand predictions for charging stations, and a global scenario of charging infrastructure design. The use of GNN for new EV charging station placement recommendation and LSTM for demand forecasting is highlighted in this research.

Keywords
GNN, demand forecasting, LSTM

1. Introduction

As the popularity of EVs grows globally, Nepal has also witnessed a gradual increase in the adoption of electric vehicles. The government has implemented various policies and incentives to encourage the purchase and use of EVs, such as reduced import taxes, customs duty exemptions, and incentives for EV manufacturing and charging infrastructure development. These initiatives have resulted in a modest but promising growth in the electric vehicle market in Nepal. However, the lack of a robust electric vehicle charging infrastructure remains a significant hurdle in the widespread adoption of EVs. Charging infrastructure plays a crucial role in alleviating range anxiety, enabling long-distance travel, and supporting the overall convenience and accessibility of EVs for both urban and rural areas. Currently, Nepal's electric vehicle charging infrastructure is in its nascent stage. The number of charging stations is limited, and they are primarily concentrated in major cities like Kathmandu and Pokhara. Most charging stations offer standard charging speeds, which can be time-consuming for EV owners, especially during peak time. Furthermore, the absence of a standardized charging network and the limited availability of fast-charging stations pose additional challenges for EV users. The unplanned positioning of Electric Vehicle charging stations in the distribution network poses a number of technical and economic challenges. The various technical concerns includes harmonic injections, poor power quality, variations in system voltage, stability[1], reliability degradation[2], etc.

To address these limitations and promote the growth of EVs, it is imperative to develop an extensive and reliable electric vehicle charging infrastructure across the country. A robust charging network would not only enhance the convenience and usability of EVs but also attract more potential buyers and create a positive ecosystem for sustainable transportation. To achieve this, it is crucial to draw insights from successful international case studies that have effectively implemented electric vehicle charging infrastructure in countries with similar socio-economic and geographical characteristics as Nepal. By learning from their experiences, Nepal can adopt best practices, overcome implementation challenges, and design a tailored approach to suit its unique requirements. Moreover, the formulation of supportive policies and regulations is essential to encourage private sector participation, incentivize investments in charging infrastructure, and ensure compatibility and interoperability among different charging networks. Additionally, exploring advanced technologies, such as fast charging, smart grid integration, and renewable energy integration, can further optimize the efficiency and sustainability of Nepal's electric vehicle charging infrastructure.

2. Literature Review

2.1 Theoretical Background

2.1.1 Overview of Electric Vehicle Charging Station

The Electric Vehicle charging station comprises of power utility grid, transformer, charging equipment, Electric Vehicle charger, energy meter, software system, network operating center and other relevant components [3].

Electric Vehicle charging equipment provides different power output for Electric Vehicle charging. Based on the power output of charging equipment, four modes of charging were defined in international standard IEC 61851-1 [4].

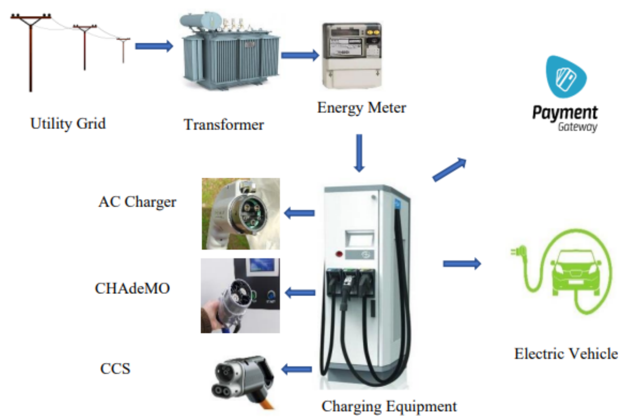

Figure 1: Overview of Charging Station

Table 1: IEC 61851-1 Charging Modes

Charging Mode	Maximum Current / Phase	Charging Time	Vehicle Battery Charger Board
Mode 1	16A (AC)	4-8 h.	ON
Mode 2	32A (AC)	2-4 h.	ON
Mode 3	63A (AC)	1-2 h.	ON
Mode 4	400A DC	30 m.	OFF

2.1.2 Existing EV charging network in Nepal

Automakers like Hyundai, BYD, Mahindra, Kia motors and government organization Nepal Electricity Authority (NEA) are installing charging station. Nepal Electricity Authority installed 50 charging station with different charger modes in different locations as listed in following table.

Table 2: Province-wise NEA Charging Station numbers

S.N.	Province Name	Number of Charging Stations (By NEA)
1	Koshi	5
2	Madhesh	7
3	Bagmati	20
4	Gandaki	6
5	Lumbini	8
6	Karnali	1
7	Sudhur-Paschim	3

2.1.3 Graph Neural Networks (GNNs)

GNNs are deep learning-based algorithms based on graph domains. GNN has lately become a popular graph analysis tool due to its impressive performance. we denote a graph as:

$$G = (V, E),$$

where,
$|V| = N$ is the number of nodes in the graph and
$|E| = N^e$ is the number of edges.

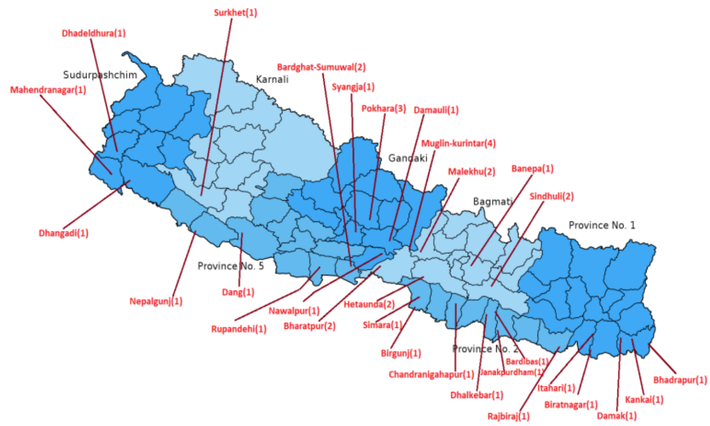

Figure 2: Locations of Charging Stations by NEA

$A \in R^{NxN}$ is the adjacency matrix.

h_v and o_v are used as the hidden state and output vector of node v for graph representation.

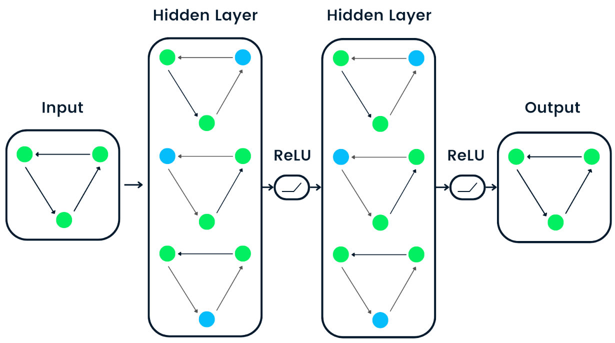

Figure 3: Graph Neural Network

2.1.4 LSTM Model

LSTM is an effective method to solve the problem of long-range dependencies, and it has universal applicability in various learning and prediction problems. In LSTM Model 3 gates are designed in the cell named input gate i_t, forget gate f_t and output gate o_t, respectively, for maintaining and updating valuable information of the data before time t. The model training method for LSTM is the well adopted back-propagation through time (BPTT) [5]. The cell states and parameters' updating scheme is as :

$$(f_t) = \sigma(W_f * [h_{t-1}, X_t] + b_f) \tag{1}$$
$$(i_t) = \sigma(W_i * [h_{t-1}, X_t] + b_i) \tag{2}$$
$$(\tilde{C}_t) = tanh(W_c * [h_{t-1}, X_t] + b_c) \tag{3}$$
$$(C_t) = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{4}$$
$$(o_t) = \sigma(W_o * [h_{t-1}, X_t] + b_o) \tag{5}$$
$$(h_t) = o_t * tanh(C_t) \tag{6}$$

where $h_{t-1}$is the output at t-1 time slot, and x_t is the current input, and $C_{t-1}$is the memory from preceding block. The forget gate (f_t) examines the information in h_{t-1} and x_t , then outputs a value between 0 and 1 for the cell state C_{t-1}, and 1 denotes "completely reserved" and 0 represents "completely discarded". The output gate o_t finally outputs a value that determines the cell state, where W and b are weight and bias. σ and $tanh$ are activation functions as:

$$(\sigma(x)) = \frac{1}{(1+e^{-x})} \tag{7}$$

$$(\tanh(x)) = \frac{(e^{x}-e^{-x})}{(e^{x}+e^{-x})} \tag{8}$$

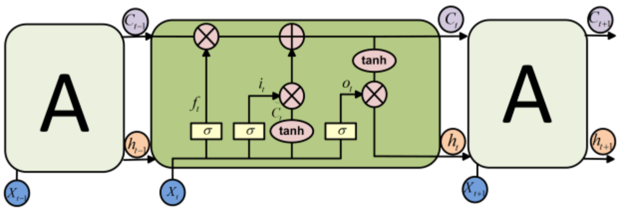

Figure 4: Structure of LSTM

2.2 Related works

Jha et al.[6] methodology for optimal placement and sizing of CSs and optimal capacitor allocation in the distribution network to improve system parameters such as power loss, voltage stability index, voltage sensitivity factor, cost of capacitor, and cost of charging station.

Roy et al. [7] achieved the highest predictive accuracy (94.9%) of EVCS placement density at a spatial resolution of 3 km using Random Forests. The findings revealed that a total of 11.04 percent of expected EVCS installations in Orange County were located inside a high spatial inequity zone, implying that communities with the least accessibility may demand more investments in EVCS placements.

Bitencourt et al. (2021)[8] developed a method for determining the best location for EV semi-fast charging stations (CS) at the neighborhood level, employing a multi-objective approach with the application of a hierarchical clustering method for EVCS location optimization by planning horizons defining CS service zones, while taking both technical and mobility aspects into account.

Guangyou et al.[9] revealed the results of the genetic algorithm-based charging station location optimization model. The model was used to predict the ideal charging station distribution in Ireland, taking into consideration parameters such as charging station depreciation, charging station power consumption per unit distance, and vehicle charging likelihood.

Xiong, et al. (2017) [10] proposed a game theoretical framework for optimal placement of electric vehicle (EV) fast charging stations considering the competitive and strategic charging practices of EV users. The author developed the Charging Station Placement Problem (CSPP) as a bilevel optimization problem and transformed it to a single-level one utilizing the EV charging game's equilibrium. The author also presented a heuristic method OCEAN with Continuous variables to deal with large-scale real-world situations called Optimizing eleCtric vEhicle chArging statioN (OCEAN). The comprehensive trials done in the research demonstrated that the proposed strategy greatly outperforms baseline methods.

Luo et al. [11] suggested a Monte Carlo simulation-based methodology to forecast the charging load of PEVs in China.

Lu et al. [12] used a random forest algorithm to estimate the 15 minute level EV charging data. However, it is difficult to quantify the external elements that affect the charging load of PEVs using traditional methods, therefore establishing a deterministic model is unfeasible.

Boulakhbar et al.[13] proposed a deep learning approach to predict the power demand of electric vehicle charging stations in regulated electricity markets, specifically in Morocco. The author used a dataset of 2000 observations of charging events collected from two public charging stations in Morocco to compare the performance of four deep learning models in predicting charging demand for EV users after a charging session begins, namely ANN, RNNs, LSTM, and GRUs.

X. Huang et al.[14] proposed a novel ensemble learning-based forecasting model by combining three base learners including the ANN, RNN, and LSTM algorithms. Specifically, a linear regression (LR) algorithm is used to learn the weight of each base learner.

3. Methodology

3.1 Block diagram

Figure 5 depicts the complete block diagram of the proposed research paper which consits as: Data collection, data Pre-processing, Construction of Graph (GNN), load forecasting (Lstm Model), optimization and recommend new station palcement, evaluation metrices and visualization graphs.

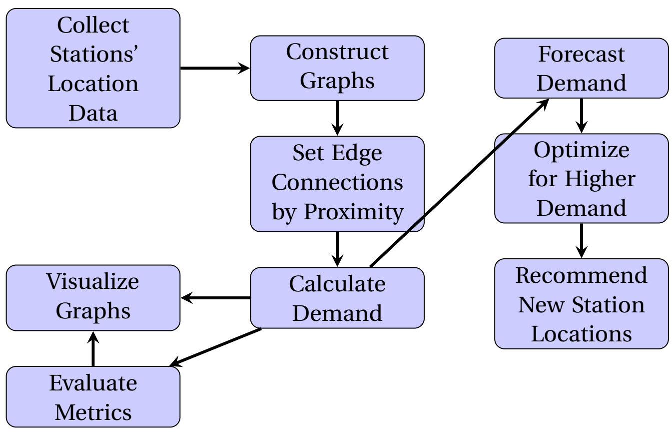

Figure 5: Block Diagram for Charging Station Data Analysis and Optimization

3.2 Data collection

- Gathering comprehensive data on population density, traffic patterns, existing NEA charging stations, geographic information, power supply capacity, historical charging patterns, and any other relevant factors.

- Exploring and analyzing the collected data to gain insights into patterns, trends, and correlations.

3.3 Data Processing

- Perform data cleaning, handling missing values, outliers, and data inconsistencies.

- Conduct feature engineering to extract meaningful features from the collected data, such as time-based features, spatial features, or derived features.

3.4 Model Development

3.4.1 Graph Construction

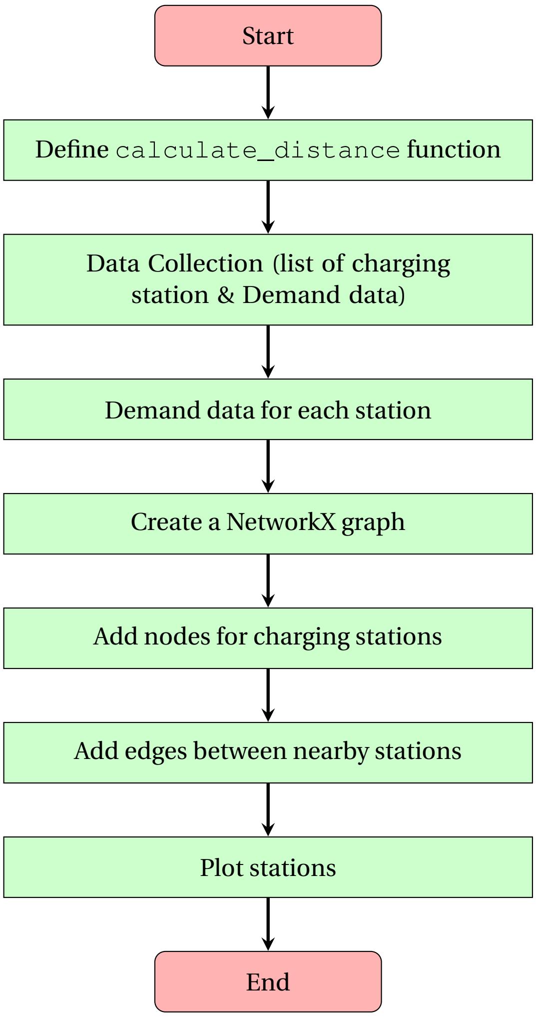

Figure 6: Flowchart for the Graph construction(GNN)

Figure 6 depicts the work flow of graph construction with necessary data collection and data preprocessing. Using NetworkX libraries, GNN model creates graph along with the edges between station. With the proximity, using haversine formula , distances are calculated and as per threshold value edge connections are performed and plotted.

3.4.2 Load Forecasting Model

Figure 7 depicts the flowchart for LSTM Model for Load Forecasting. The collected data are prepared with necessary data pre-processing and feature engineering.Demand data converted to Pytorch tensors and dataloaders are created. Forecasting of future demand is performed and forward passed to the combined model.

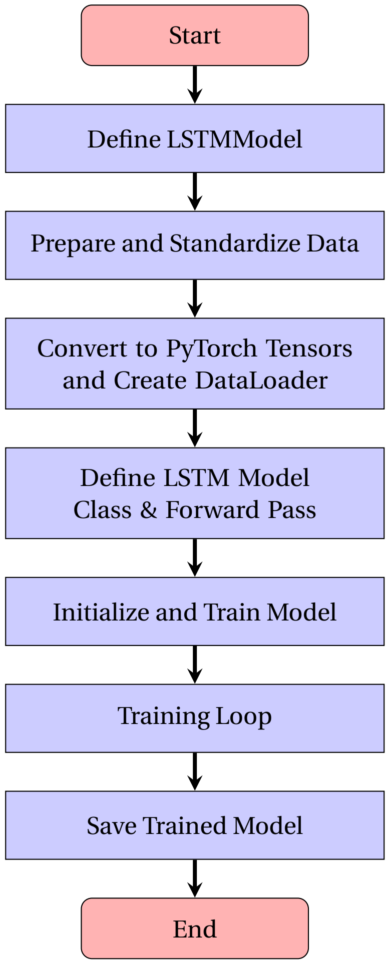

Figure 7: Flowchart for LSTM Model (Load Forecasting)

3.4.3 Combination of LSTM and GNN

The forward pass values from the lstm model are the input feature for the GNN Model.Each station are mapped to indices demand are evaluated and updated and thereby new demand is predicted.This updates the node features and are converted to PYtorch geometric objects, The GNN model takes input from lstm model and provide coordinates of recommended new station placement that meets the distribution of load of nearby stations.

3.5 Evaluation Techniques

There are number of performance measures that are used for evaluating model accuracy. Among the commonly used error evaluation functions, root mean squared error (RMSE) and mean absolute error (MAE) are applied for evaluating model performance in load forecasting. RMSE enables us to penalize outliers and clearly interpret the forecasted output, as they are in the same unit as the feature that the model is predicting. The equation of RMSE is:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(\tilde{y}_i - y_i)^2} \tag{9}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{n}|\tilde{y}_i - y_i| \tag{10}$$

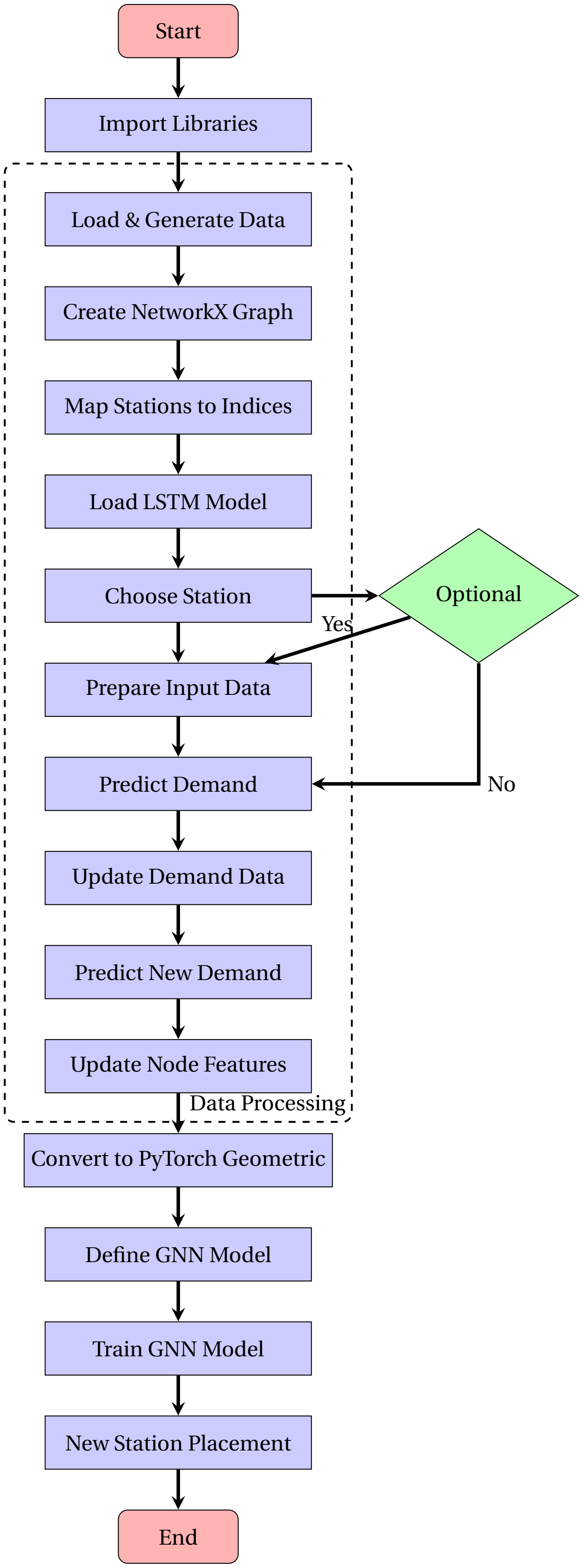

Figure 8: Combined LSTM & GNN Flowchart

4. Result Analysis and Discussion

Collecting from 32 charging station considering load(energy in kwh) for respective charging time, dataset was prepared. Each charging station with their latitude and longitude, distance was calculated usiing Haversine formula and graph was constructed with charging station as node.

Figure 9 illustrates the construction of graph using graph neural network(GNN).In this Graph the stations are connected by edges that are located under 50 km.

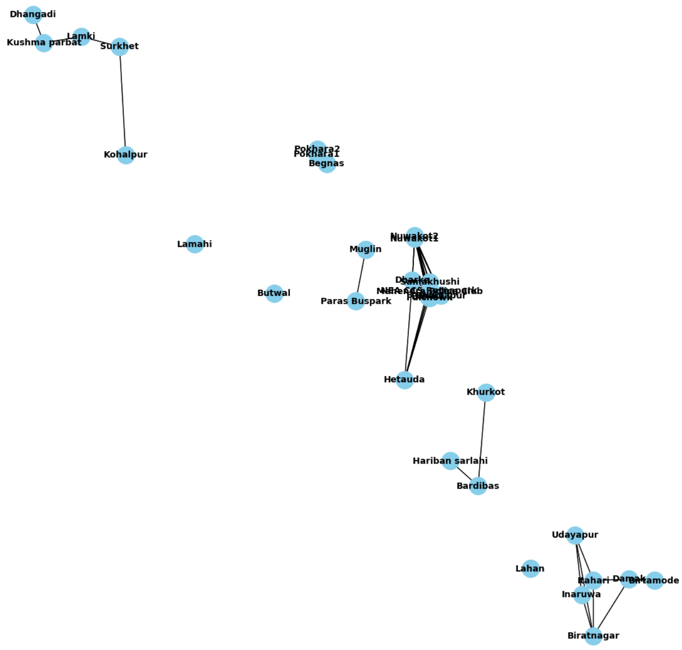

Figure 9: Charging station construction in graph with edges (located within 50km)

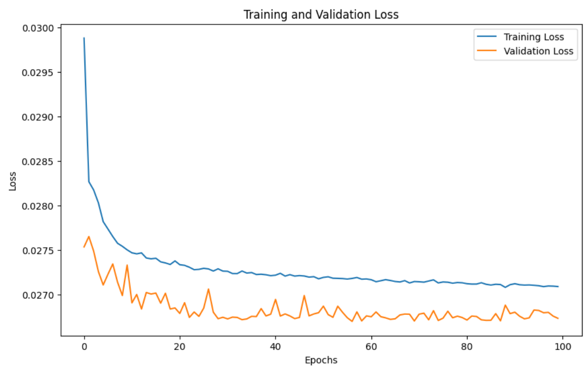

Figure 10: training and validation loss over 100 epochs

Figure 10 depicts the training and validation loss over epochs for load forecasting using LSTM model. It shows that validation loss is lower than traininng loss and both are gradually decreasing over 100 epochs.

Table 3 shows the the predictive results of RMSE, MAE and MSE score. For these evaluation metrices, a lower value of RMSE and MAE corresponds to the better peformance of the forecasting model. The values of RMSE, MAE and MSE score shows that capturing uncertainity in load forecasting for an EV charging station is significant.

Table 3: Evaluation metrices result

S.N.	Evaluation Metrices	Value
1	Mean Absolute Error (MAE)	1.6379
2	Mean Square Error(MSE)	3.87511
3	Root Mean Square Error(RMSE)	1.96853

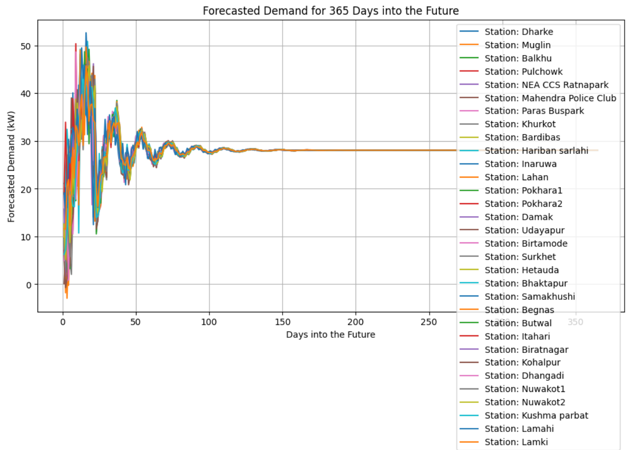

Figure 11: Forecasted demand of all CS for future 365 days

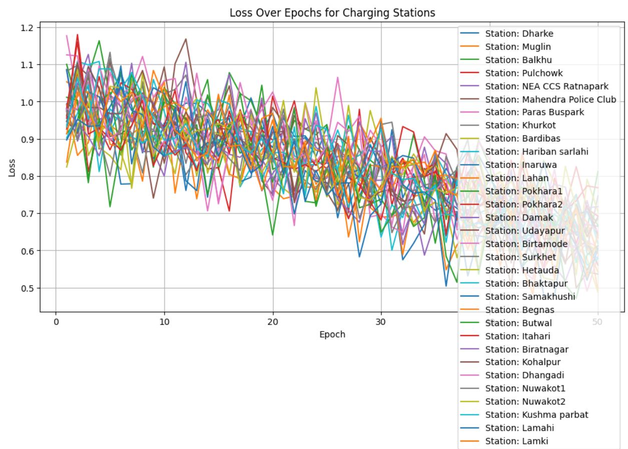

Figure 12: Loss over epochs of all Charging stations

Figure 11 illustrates the forecasting of demand of all charging statons for a year(365 days). Using LSTM (Long Short Term Memory) model demand of each 32 charging station are forecasted for 365 days.
Figure 12 depicts the losses over 50 epochs of all charging stations. The losses has been gradually decreasing over the epochs. All 32 charging station demand load data are processed and accordingly with LSTM model, future demand are forecasted with losses.The losses for all charging station are plotted with different colors to distinguish them,

4.1 Example: Itahari Charging Station)

Taking the case for Itahari Charging station; forecasting of demand over a year was performed using LSTM Model. Figure 13 illustrates the actual versus forecasted demand of Itahari Charging station. For 150 days collected data, actual load is plotted along with forecasting demand for 365 days.
Figure 14 depicts the graph plot showing training and test loss over 150 epochs. It seems training loss seems higher in initial epochs and further training over iterations resulted in lower training loss.

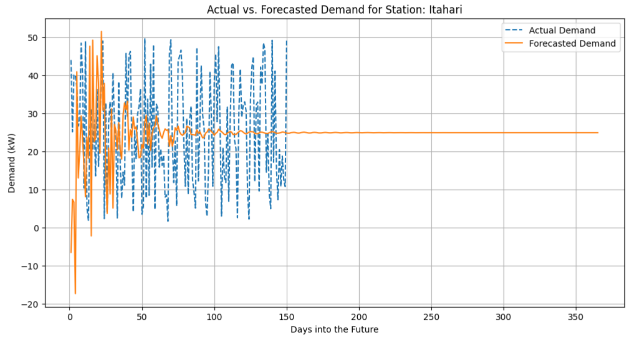

Figure 13: Itahari CS Actual vs Forecasted demand

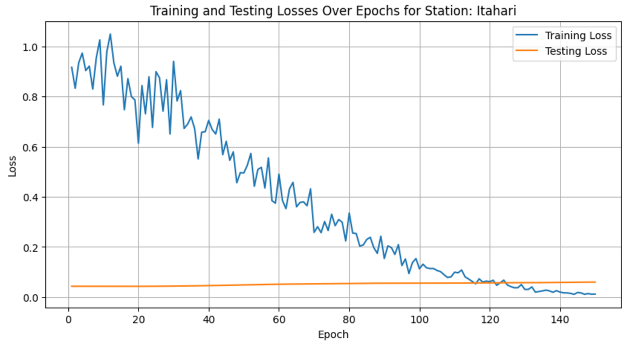

Figure 14: Itahari CS Training & Test Loss over epochs

After forecasting of demand of each node, those forecasted demand values are then forward passed to the GNN model. GNN model are trained and 5 recommended new charging station along with monthly predicted demand value is obtained as in shown in table 4. This table shows sample for new recommendation stations that are located in the Koshi province.

Table 4: Recommendation of new charging station

S.N.	New Station	Lat.	Long.	Pred.Demand
1	Belbari	26.658	87.422	3440.67
2	Dharan	26.835	87.298	2510.39
3	Dharan	26.791	87.290	2379.05
4	Dhankuta	26.877	87.331	1870.55
5	Hile	27.021	87.314	369.99

Figure 15 depicts the graph showing the network of existing NEA Charging station and new recommendation of placement of charging station. As taking sample of 5 new recommendation stations, predicted result is the location as Belbari, Dharan, Dhankuta, Hile. Among them Hile new station has lower predicted demand value and Belbari with higher value. It shows Belbari station is highly recommended for the placement of charging station and thereby Dharan.

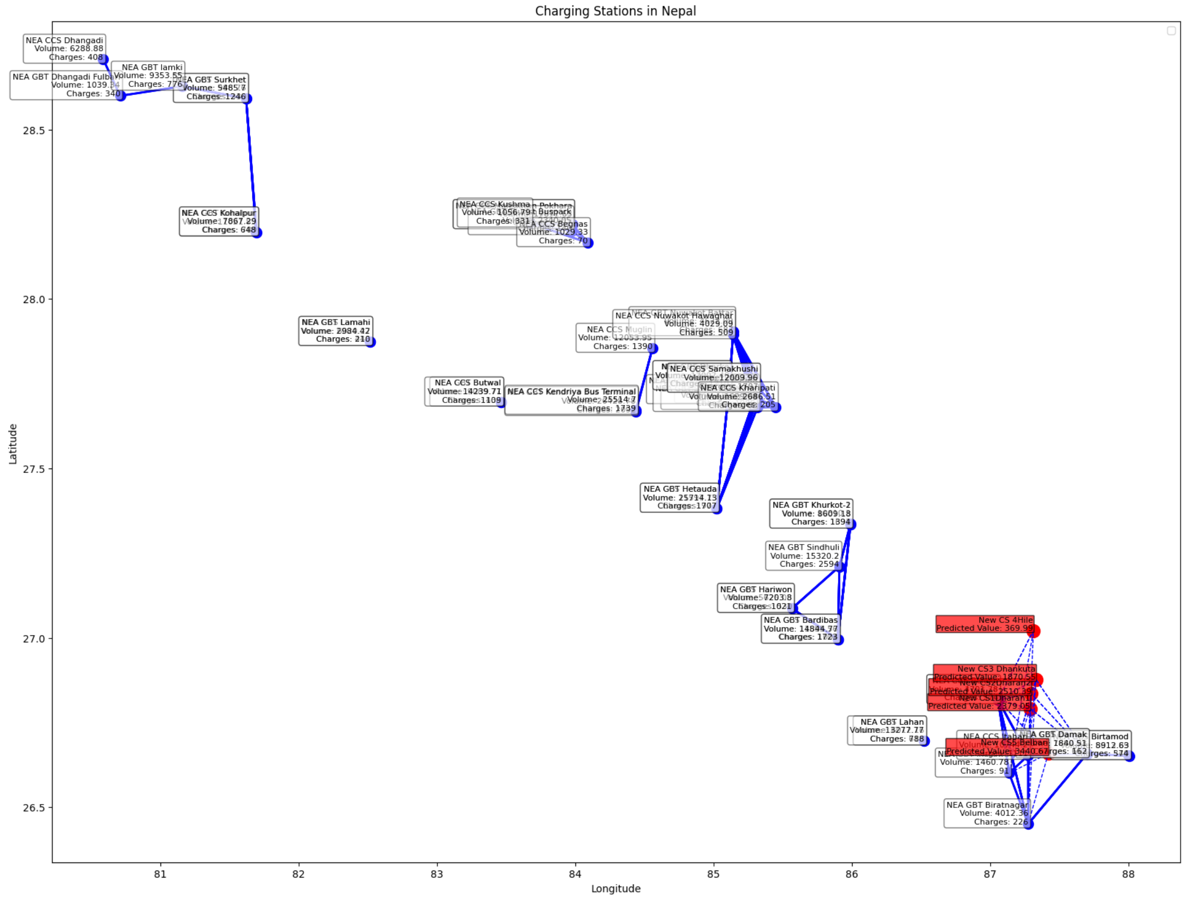

Figure 15: Construction of graph showing existing and new charging station (recommendation)

5. Conclusion

In conclusion, using geographic data, demand forecasts, and graph-based deep learning approaches, the proposed research paper presents a robust methodology for optimizing the placement of charging stations. An LSTM-based demand prediction model and algorithms to calculate distances between geographic coordinates are incorporated in data preparation. Then, based on geographic proximity, it creates a NetworkX graph to represent charging stations and their connections. The retrieved and standardized node features are then used to create a PyTorch Geometric Data object. The ChargingStationGNN model, a multi-layered Graph Neural Network that learns to anticipate ideal station placements, is the basis of the suggested study. Through the Adam optimizer, mean squared error loss is reduced during model training. Finally, forecasts are generated of each charging station. This paper has the opportunity for customization and integration to enhance its practical utility. It serves as a core framework for tackling practical charging station placement difficulties.

Acknowledgments

The successful completion of this project owes gratitude to the contributions and support of numerous individuals and organizations(Nepal Electricity Authority). Special thanks to the open-source communities behind NetworkX, PyTorch, and Scikit-learn for providing essential tools and libraries. Furthermore, grateful to invaluable guidance and insights from peers and mentors, greatly influencing the development of this code. This project stands as a testament to their collective efforts and expertise, and it would not have been achievable without their support.

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Appendix

Total input values were gathered and collected from Nepal Electricity Authority, Transport management office, & Google Maps for coordinates and necessary pre-processing of data were performed for relevant information.