Intelligent Control and Automation, 2024, 15, 63-82
https://www.scirp.org/journal/ica
ISSN Online: 2153-0661
ISSN Print: 2153-0653

Prediction and Analysis of Elevator Traffic Flow under the LSTM Neural Network

Mo Shi[1], Entao Sun[2], Xiaoyan Xu[3], Yeol Choi[1]

[1]School of Architecture, Kyungpook National University, Daegu, Republic of Korea
[2]School of Software Engineering, East China Normal University, Shanghai, China
[3]HaXell Elevator Co., Ltd., Shanghai, China
Email: shimo0204@outlook.jp

How to cite this paper: Shi, M., Sun, E.T., Xu, X.Y. and Choi, Y. (2024) Prediction and Analysis of Elevator Traffic Flow under the LSTM Neural Network. *Intelligent Control and Automation*, **15**, 63-82.
https://doi.org/10.4236/ica.2024.152004

Received: April 28, 2024
Accepted: May 21, 2024
Published: May 24, 2024

Copyright © 2024 by author(s) and Scientific Research Publishing Inc.
This work is licensed under the Creative Commons Attribution International License (CC BY 4.0).
http://creativecommons.org/licenses/by/4.0/
Open Access

Abstract

Elevators are essential components of contemporary buildings, enabling efficient vertical mobility for occupants. However, the proliferation of tall buildings has exacerbated challenges such as traffic congestion within elevator systems. Many passengers experience dissatisfaction with prolonged wait times, leading to impatience and frustration among building occupants. The widespread adoption of neural networks and deep learning technologies across various fields and industries represents a significant paradigm shift, and unlocking new avenues for innovation and advancement. These cutting-edge technologies offer unprecedented opportunities to address complex challenges and optimize processes in diverse domains. In this study, LSTM (Long Short-Term Memory) network technology is leveraged to analyze elevator traffic flow within a typical office building. By harnessing the predictive capabilities of LSTM, the research aims to contribute to advancements in elevator group control design, ultimately enhancing the functionality and efficiency of vertical transportation systems in built environments. The findings of this research have the potential to reference the development of intelligent elevator management systems, capable of dynamically adapting to fluctuating passenger demand and optimizing elevator usage in real-time. By enhancing the efficiency and functionality of vertical transportation systems, the research contributes to creating more sustainable, accessible, and user-friendly living environments for individuals across diverse demographics.

Keywords

Elevator Traffic Flow, Neural Network, LSTM, Elevator Group Control

1. Introduction

Elevator traffic congestion remains a significant challenge, especially in densely populated urban areas and high-rise buildings. Urbanization has led to an increase in high-rise buildings, resulting in higher demand for elevators. In densely populated cities, such as New York City, Tokyo, or Shanghai, elevators experience heavy usage throughout the day, particularly during peak hours such as morning and evening rush hours. However, many older buildings were not designed to accommodate the current volume of elevator traffic. Retrofitting additional elevators into existing structures can be costly and technically challenging due to limited physical space and structural constraints. As a result, these buildings often have fewer elevators than would be ideal for the current level of demand.

Due to these reasons, elevator traffic management stands as a persistent concern in densely populated urban centers and towering high-rise structures, exerting profound impacts on operational efficiency, passenger safety, and overall user experience. The complexity of elevator traffic dynamics is influenced by a multitude of factors, including building occupancy levels, architectural design nuances, maintenance protocols, and ongoing technological innovations. In particular, the relentless trend of urbanization coupled with the proliferation of increasingly tall buildings has exacerbated the demand for robust and efficient elevator systems capable of coping with escalating passenger volumes. The overarching challenge lies not only in swiftly and securely transporting individuals between floors but also in these movements to minimize wait times and alleviate congestion, particularly during peak periods of demand.

Over the decades, the study of elevator traffic has garnered significant attention from researchers worldwide, prompting the exploration of diverse analytical methodologies and simulation techniques aimed at unraveling its complexities and devising effective solutions. These endeavors encompass a spectrum of approaches, ranging from mathematical modeling and algorithmic optimization to sophisticated computer simulations and empirical studies conducted within real-world settings.

According to Fei Luo *et al.* [1], an in-depth analysis of elevator traffic within a standard office building was undertaken, employing a methodology centered around the application of LS-SVMs (Least Squares Support Vector Machines). The investigation involved the systematic sampling of traffic flow data at 5-minute intervals spanning the operational hours from 7:00 to 19:00 daily, resulting in a comprehensive dataset comprising 144 data points for each day under examination. Given the inherent variability and stochastic nature of real-world traffic flow data, measures were implemented to mitigate the impact of noise and ensure the robustness of the analysis. To this end, a segmentation strategy was adopted, wherein three weeks' worth of traffic data was allocated for training purposes, allowing the LS-SVMs to discern underlying patterns and dynamics from the observed traffic behaviors. Subsequently, an additional week of traffic data was reserved for testing, enabling the evaluation of the model's predictive capabilities and generalization performance under real-world conditions.

Central to the efficacy of LS-SVMs lies the choice of the kernel function, which plays a pivotal role in shaping the model's predictive performance and adaptability to diverse datasets. In this regard, Fei Luo *et al.* [1] investigation placed particular emphasis on the RBF (Radial Basis Function) kernel as below:

$$K(x,y)=\exp\left(-\frac{\|x-y\|^2}{2\sigma^2}\right) \tag{1}$$

Referring to the research of Fei Luo *et al.* [1], employs MSE (Mean Square Root Errors) as a performance index to assess prediction results obtained using LS-SVMs as below:

$$\text{MSE}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left|Y_i-Y_{i*}\right|^2} \tag{2}$$

where Y_i is the actual value and Y_{i*} is the predicted value.

Furthermore, Zhifeng Pan *et al.* [2] proposed an elevator traffic flow model grounded in dynamic passenger distribution, highlighting the significance of dynamic traffic flow within elevator systems as below:

$$\eta_{ij}=\frac{POP(j)*\left(1+\varphi(j)\right)-PIF(j)}{\sum\limits_{\substack{K=2\\K\neq j}}^{N}\left[POP(K)*\left(1+\varphi(K)\right)-PIF(K)\right]} \tag{3}$$

where $PIF(j)$ represents the number of people on the ith floor, $POP(j)$ denotes the passenger distribution capability rating of the jth floor, $\varphi(j)$ refers to the over-loading modulus of the jth floor's passenger distribution capability, and N signifies the total number of floors in the building.

Furthermore, Ahmad Hammoudeh *et al.* [3] utilized Gaussian analysis to create a real-time estimator for passenger arrival rates to elevator systems, providing a valuable reference for elevator traffic analysis.

In the wake of rapid advancements in neural network technology, the landscape of traffic analysis has undergone a profound transformation, marked by the integration of cutting-edge AI algorithms into traditional analytical frameworks. Especially, at the forefront of this transformative wave is the adoption of LSTM (Long Short-Term Memory) networks within RNN (Recurrent Neural Network) convolutional architectures [4]-[9]. LSTM's inherent ability to capture long-range dependencies and temporal patterns makes it particularly well-suited for modeling and forecasting complex traffic dynamics with high accuracy and reliability. By leveraging LSTM's capacity for sequential data processing, researchers can extract valuable insights from vast streams of traffic data, enabling more informed decision-making and resource allocation in urban planning, transportation management, and infrastructure development [10]-[15]. This research employs LSTM technology in the analysis of elevator traffic dynamics.

Leveraging the unique characteristics of neural networks, LSTM facilitates the prediction of future traffic patterns within elevator systems. By extrapolating from historical elevator traffic data, LSTM models can generate accurate forecasts of elevator usage, aiding in proactive decision-making for the elevator group control system.

The foundation of this research lies in Fei Luo *et al.* [1] on elevator traffic analysis, which laid the groundwork for understanding the intricacies of passenger flow within office buildings. Building upon the insights garnered from Fei Luo *et al.* [1] and leveraging the predictive capabilities demonstrated by LS-SVMs, this research delves deeper into the realm of elevator traffic dynamics, with a particular emphasis on harnessing the potential of LSTM (Long Short-Term Memory) neural network technology.

To advance the understanding of elevator traffic dynamics, this research undertakes a comprehensive reanalysis of real-world data obtained from monitored operations within typical office buildings. The dataset, comprising empirical observations collected during daytime hours from 7:00 to 18:30 as **Figure 1** illustrates, serves as a significant source of information ripe for analysis in this research.

This research lies in the utilization of LSTM (Long Short-Term Memory) predictors to analyze elevator traffic dynamics, leveraging a comprehensive dataset comprising 655 points of actual monitored data collected over the course of a full day. Within this dataset, particular attention is directed towards three distinct peak periods corresponding to heightened passenger flow: the morning rush, noon rush, and end-of-day rush.

To facilitate the training of the LSTM predictor, 200 points of data from the morning rush are earmarked, serving as a representative sample for capturing the underlying patterns and dynamics of peak-hour traffic. The remaining 455 points from the noon rush and end-of-day rush are allocated for the prediction

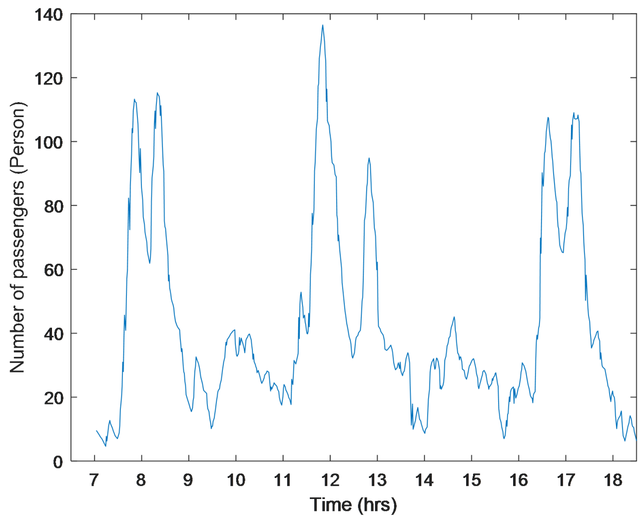

Figure 1. Elevator traffic flow.

process, enabling the LSTM model to extrapolate future traffic trends based on learned patterns from the training dataset.

A crucial aspect of this research involves the comparison of training and prediction results obtained from the LSTM predictor with actual monitored data. By conducting this comparative analysis, the research aims to assess the accuracy and reliability of the LSTM model in capturing and forecasting elevator traffic dynamics across different time intervals and peak periods.

Moreover, this research underscores the transformative potential of neural network technology, particularly LSTM, in the domain of elevator traffic analysis. By harnessing the predictive capabilities of LSTM, researchers can gain valuable insights into passenger flow patterns, optimize elevator operations, and enhance the overall passenger experience within urban environments. Through an iterative process of empirical analysis and computational modeling, this research endeavors to bridge the gap between theory and practice within the domains of vertical transport engineering.

For decades, elevator group control systems have served as essential tools for alleviating the stress caused by elevator traffic congestion. These systems play a crucial role in optimizing elevator operations, minimizing wait times, and enhancing passenger experience within vertical transportation systems. However, as urbanization and building construction continue to intensify, the need for innovative solutions to address elevator traffic challenges becomes increasingly pressing.

In this research endeavor, the focus is on harnessing LSTM technology to provide actionable insights and data-driven recommendations for improving elevator group control systems. By analyzing historical elevator traffic data and leveraging LSTM's predictive capabilities, the research aims to uncover hidden patterns, trends, and correlations within elevator flow dynamics. The overarching objective is to inform decision-making processes and facilitate the development of more efficient, sustainable, and user-centric vertical transportation systems. By offering actionable insights derived from LSTM analysis, the elevator group control system can make informed decisions to optimize elevator operations, reduce congestion, and enhance passenger satisfaction.

2. Structure and Theory of the LSTM

An LSTM (Long Short-Term Memory) network stands out as a sophisticated variant of the RNN (Recurrent Neural Network) structure. Its distinction lies in its capability to tackle the challenge of long-term dependency, a hurdle that conventional RNNs struggle to overcome. While RNNs exhibit effectiveness in tasks involving sequence prediction, they often falter when confronted with the complexities of identifying long-term patterns within sequential data. LSTM networks, on the other hand, excel in such scenarios owing to their unique architectural components, notably the inclusion of forget gates and state vectors. These specialized mechanisms empower LSTM networks to not only retain but also selectively update and discard information over extended sequences, thereby enhancing their ability to learn intricate patterns and dependencies within sequential data. Through the strategic integration of these components, LSTM networks emerge as powerful tools for processing sequential data, offering superior performance and efficiency compared to RNN.

Within the architecture of an LSTM unit, the memory cell (C_t) stands as a crucial component responsible for preserving information from the current time step (t). This memory cell is intricately connected to various other components within the LSTM unit, facilitating the flow and manipulation of information throughout the network. In the context of sequence processing, let x_t represent the input vector at time step t, h_t denotes the output of the LSTM unit, and C_t signifies the cell state at time t.

During each iteration, a pivotal decision regarding memory retention occurs through the operation of the forget gate. This gate, functioning as a layer within the LSTM unit, employs a sigmoid activation function. By leveraging inputs from the previous cell state (C_{t-1}) and the current input vector (x_t), the forget gate computes a value, denoted as f_t, which ranges between 0 and 1. This value effectively dictates the extent to which information from the previous cell state (C_{t-1}) will be retained or forgotten as the network progresses to the next time step. Therefore, the forget gate plays a pivotal role in regulating the flow of information within the LSTM unit, ensuring the selective preservation or discarding of pertinent data based on the context of the input sequence, and f_t in **Figure 2** can be written as:

$$f_t = \sigma\left(W_f \cdot \left[h_{t-1}, x_t\right] + b_f\right) \tag{4}$$

Following the process of determining which information to retain and which to discard, the subsequent phase in the LSTM framework is dedicated to incorporating new information into the cell state. This critical step unfolds in two distinct sub-steps, each serving a specific purpose in the information updating process.

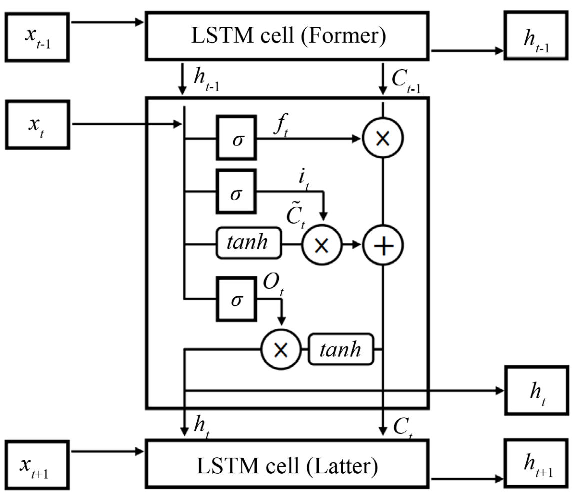

Figure 2. Framework of LSTM network.

The first sub-step revolves around the operation of the input gate. This gate (i_t) assumes the responsibility of scrutinizing the incoming data stream and determining which pieces of information are pertinent for updating the cell state. By leveraging its functionality, the input gate selectively filters and prioritizes relevant information, thereby facilitating the integration of new data into the LSTM unit. Subsequently, the second sub-step focuses on generating a vector comprising candidate values. This vector (C_t) serves as a reservoir of potential updates to the cell state, providing a diverse array of options for enhancing the network's understanding of the input sequence. Through this mechanism, the LSTM unit ensures a dynamic and adaptive approach to information processing, enabling it to capture nuanced patterns and dependencies within sequential data with greater accuracy and efficiency.

In the representation depicted in **Figure 2**, the output values of these sub-steps are denoted by symbols i_t and C_t, respectively. These outputs encapsulate the culmination of the input gate's decision-making process and the generation of candidate values, laying the groundwork for the subsequent refinement and augmentation of the LSTM unit's cell state. In order to understand, i_t and C_t can be written as follows:

$$i_t = \sigma\left(W_i \cdot \left[h_{t-1}, x_t\right] + b_i\right) \tag{5}$$

$$\tilde{C}_t = tahn\left(W_C \cdot \left[h_{t-1}, x_t\right] + b_C\right) \tag{6}$$

Following the preceding steps in the LSTM process, the previous state vector (C_{t-1}) undergoes updates to yield the new state vector (C_t), and the update process can be written as:

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{7}$$

The output gate (o_t) decides which aspects of the cell state will contribute to the output and can be written as:

$$o_t = \sigma\left(W_o \cdot \left[h_{t-1}, x_t\right] + b_o\right) \tag{8}$$

The final stage involves determining the hidden state (h_t).

$$h_t = o_t * tahn\left(C_t\right) \tag{9}$$

In the complete LSTM process, σ represents the sigmoid function, $W_{(f,i,c,o)}$ matrices denote network parameters, $b_{(f,i,c,o)}$ signify bias matrices, and $*$ indicates the product operation. These components enable LSTM to effectively address the challenge of exploding or vanishing gradients.

3. Discussion of the LSTM Results

3.1. Coding Process

In the intricate process of coding and implementing the predictive model, the division of the 655 actual monitored data points assumes paramount importance. This meticulous division strategy enables researchers to effectively train and evaluate the performance of the LSTM (Long Short-Term Memory) model in predicting elevator traffic dynamics.

As Figure 3 illustrates, within the scope of this research, a subset comprising 200 data points is earmarked for the training phase of the LSTM model. These data points serve as the foundation for imparting the necessary insights and patterns to the model, enabling it to learn and adapt to the underlying dynamics of elevator traffic flow during peak periods. Subsequently, the remaining 455 data points are reserved for the testing phase, wherein the trained LSTM model is tasked with predicting elevator traffic patterns based on the acquired knowledge and learned parameters. This testing phase serves as a critical evaluation mechanism, allowing researchers to gauge the accuracy, robustness, and generalization capabilities of the LSTM model in forecasting elevator traffic dynamics across different time intervals and scenarios.

Moreover, within this framework, a specific training protocol is established, wherein the LSTM model is trained using a subset of 10 data points, followed by the prediction of 1 subsequent point after each training cycle. This iterative training and prediction cycle encapsulates the essence of the LSTM model's learning process, wherein the model iteratively updates its internal parameters and adapts to the underlying patterns and dynamics of the elevator traffic data.

Referring to Figure 4, the modeling process begins with the specification of an input layer comprising 10 units, which serves as the conduit for ingesting and processing the sequential input data representing elevator traffic dynamics. Subsequently, the LSTM model features a hidden layer consisting of 10 units, which

```
temp = 1: 1: 655;

P_train = res(temp(1: 200), 1: 10)';
T_train = res(temp(1: 200), 11)';
M = size(P_train, 2);

P_test = res(temp(201: end), 1: 10)';
T_test = res(temp(201: end), 11)';
N = size(P_test, 2);
```

Figure 3. Data divide (train and test).

```
layers = [
    sequenceInputLayer(10)

    lstmLayer(10, 'OutputMode','last')
    reluLayer

    fullyConnectedLayer(1)
    regressionLayer];
```

Figure 4. Modeling.

serves as the primary computational engine responsible for capturing and learning the temporal dependencies and patterns inherent in the input data.

Following the hidden layer, an activation function, specifically the Relu (Rectified Linear Unit), is applied. The Relu activation function introduces non-linearity into the model, enabling it to capture complex relationships within the input data more effectively. This non-linear transformation enhances the expressive power of the LSTM model, enabling it to better capture and represent the underlying dynamics of elevator traffic flow.

In the subsequent step, a fully connected layer comprising a single unit is introduced. This layer serves as the bridge between the hidden layer and the output layer, facilitating the integration of information learned by the LSTM model into a compact and interpretable representation. Finally, the regression layer is employed as the last step of the LSTM modeling process, enabling the model to generate continuous output predictions based on the learned representations and patterns extracted from the input data.

The efficacy of the LSTM (Long Short-Term Memory) model hinges crucially on the configuration of its parameters, which exert a profound influence on the model's training dynamics and predictive performance. As depicted in **Figure 5**, meticulous attention is devoted to fine-tuning these parameters to optimize the LSTM's learning process and enhance its predictive accuracy.

In this research, the Adam optimizer emerges as the optimizer of choice for training the LSTM model, leveraging its adaptive learning rate to expedite convergence and improve optimization efficiency. With a maximum of 1000 iterations stipulated for the training process, the LSTM model iteratively refines its internal parameters and updates its predictive capabilities through successive epochs of training.

Of particular significance is the design of the initial learning rate, which is set at 0.005 to facilitate rapid learning and exploration of the solution space during the early stages of training. However, to mitigate the risk of overshooting the global optimum and to promote stable convergence, a dynamic learning rate schedule is adopted. After 800 iterations, the learning rate is reduced to 0.0005, allowing the LSTM model to fine-tune its parameters with greater precision and

```
options = trainingOptions('adam', ...
    'MaxEpochs',1000, ...
    'InitialLearnRate', 5e-3, ...
    'LearnRateSchedule', 'piecewise', ...
    'LearnRateDropFactor', 0.1, ...
    'LearnRateDropPeriod', 800, ...
    'Shuffle', 'every-epoch', ...
    'Plots', 'training-progress', ...
    'Verbose', false);
```

Figure 5. Parameter setting.

control, thereby enhancing its ability to generalize and make accurate predictions on unseen data.

Figure 6 illustrates the training model, incorporating training input and output data, LSTM modeling layers, and parameters fed into the train network function.

Following the training process, by feeding the training and testing inputs into the network, leverage the learned parameters and optimized architecture of the LSTM model to compute predictions for both datasets. This computation process involves propagating the input data through the various layers of the LSTM model, where it undergoes a series of transformations and computations to generate predictions for elevator traffic dynamics.

```
%% Model training
net = trainNetwork(p_train, t_train, layers, options);

%% Simulation predictor
t_sim1 = predict(net, p_train);
t_sim2 = predict(net, p_test);
```

Figure 6. Training and predicting.

3.2. Discussion of the Results

Table 1 provides a comprehensive breakdown of the architecture underlying the train network, elucidating the arrangement of its constituent layers and the distribution of learnable properties throughout the network structure. Central to the design of the train network are five distinct layers, each playing a specialized role in processing input data and generating output predictions.

The sequence input layer serves as the entry point for ingesting sequential data representing elevator traffic dynamics, facilitating the integration of temporal information into the LSTM model. Subsequently, the LSTM layer, characterized by its memory-enhancing capabilities, captures temporal dependencies and extracts salient features from the input sequence data, enabling the model to encode complex patterns and relationships inherent in elevator traffic dynamics.

Following the LSTM layer, the Relu activation function introduces non-linearity into the network, enhancing its capacity to capture complex relationships and nonlinear patterns within the input data. This non-linear transformation facilitates the extraction of higher-order features and enhances the model's expressive power.

The fully connected layer acts as a bridge between the preceding layers and the regression output layer, facilitating the integration of information learned by the LSTM model into a compact and interpretable representation. Finally, the regression output layer generates continuous output predictions based on the learned representations and patterns extracted from the input data, serving as the ultimate decision-making component of the network.

Table 1. Structure of the train network.

Step	Type	Activations	Learnable properties	States
1	Sequence Input	10(C) × 1(B) × 1(T)	-	-
2	LSTM	10(C) × 1(B)	Input Weights (40 × 10) Recurrent Weights (40 × 10) Bias (40 × 1)	Hidden State 10 × 1 Cell State 10 × 1
3	ReLU	10(C) × 1(B)	-	-
4	Fully Connected	1(C) × 1(B)	Weights (1 × 10) Bias (1 × 1)	-
5	Regression Output	1(C) × 1(B)	-	-

Within the train network structure, learnable properties are concentrated within the LSTM and fully connected layers, where the model adapts and refines its internal parameters through the training process. These learnable properties, encompassing weights, biases, and other trainable parameters, play a crucial role in shaping the model's predictive performance and optimizing its ability to capture and forecast elevator traffic dynamics accurately. Moreover, throughout the entirety of the research endeavor, the train network encompasses a total of 851 learnables, distributed across the five layers comprising the network architecture.

Figure 7 serves as a visual representation of the outcomes derived from both the training and testing phases of the LSTM model. The graph is divided into two distinct sections, each offering insights into the model's performance during different phases of the elevator traffic analysis.

In Figure 7(a), which pertains to the morning rush period of elevator traffic, the LSTM model's predictions exhibit a remarkable degree of similarity to the actual monitored data. This close alignment between predicted and observed values underscores the model's effectiveness in capturing and forecasting elevator traffic dynamics during peak traffic periods. The results of the training phase, as evidenced by Figure 7(a), emphasize the robustness and accuracy of the LSTM model in learning from training data and generating precise predictions that closely mirror actual observations.

Similarly, in Figure 7(b), which focuses on the noon rush and end-of-day rush periods, the LSTM model once again demonstrates its prowess in predicting elevator traffic dynamics with remarkable accuracy. The predictions generated by the model closely track the observed patterns of elevator usage during these critical time intervals, validating the model's efficacy in extrapolating learned patterns to unseen data. The results of the testing phase, as depicted in Figure 7(b), serve to reaffirm the workability and generalization capabilities of the LSTM model, underscoring its ability to perform effectively in real-world scenarios beyond the confines of the training dataset.

MSE (Mean Square Error) assumes a pivotal role as a quantitative metric for assessing the accuracy and precision of LSTM models. MSE serves as a fundamental

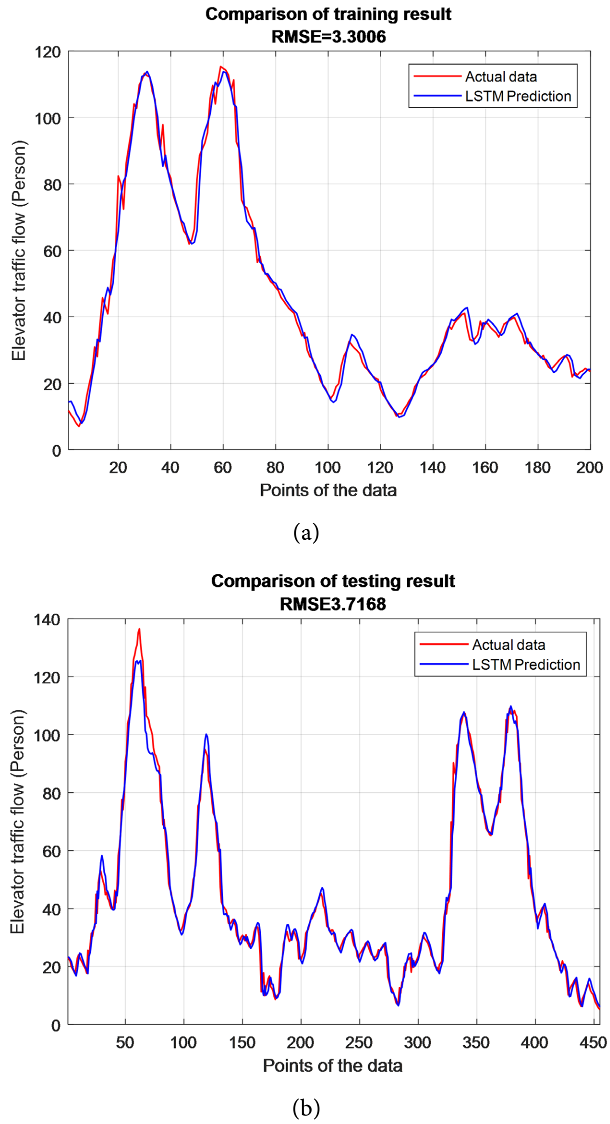

Figure 7. Comparison of training and testing. (a) Training result; (b) Testing result.

measure of the disparity between predicted and actual values within a dataset, providing valuable insights into the performance of the model in capturing the underlying patterns and dynamics of elevator traffic, and the mean squared error of MSE can be calculated as the Equation (10) below:

$$\mathrm{MSE} = \frac{1}{n} \cdot \sum_{i=1}^{n} w_i \left(y_i - \hat{y}_i \right)^2 \tag{10}$$

By quantifying the square of the differences between predicted and observed values, MSE offers a comprehensive assessment of the overall predictive accuracy of the LSTM model. Lower MSE values indicate a closer alignment between predicted and actual data points, signifying a higher degree of accuracy and reliability in the model's predictions. Conversely, higher MSE values suggest greater discrepancies between predicted and observed values, indicative of potential shortcomings or inaccuracies in the model's predictive capabilities.

Moreover, rooting the value of MSE, the value of RMSE (Root Mean Square Error) can be calculated as the Equation (11) shows below:

$$\text{RMSE} = \sqrt{\text{MSE}} = \sqrt{\frac{1}{n} \cdot \sum_{i=1}^{n} w_i \left(y_i - \hat{y}_i \right)^2} \tag{11}$$

As depicted in **Figure 7**, the RMSE serves as a crucial metric for evaluating the accuracy and precision of the LSTM model in predicting elevator traffic dynamics. In the training section, the RMSE is calculated to be 3.3006, indicating the average magnitude of prediction errors across the first 200 data points used for training. Conversely, in the testing section, the RMSE value is slightly higher at 3.7168, reflecting the average prediction error across the remaining 455 data points reserved for testing.

The disparity in RMSE values between the training and testing sections highlights the differences in predictive accuracy observed during these distinct phases of the modeling process. The lower RMSE observed in the training phase suggests a higher degree of accuracy and precision in the LSTM model's predictions when trained on a smaller subset of data. In contrast, the higher RMSE observed in the testing phase indicates a slightly reduced accuracy and predictive performance when extrapolating learned patterns to unseen data points.

Despite the discrepancy in RMSE values between the training and testing sections, it is noteworthy that the difference is not excessively pronounced. This indicates that while there may be some degradation in predictive accuracy when transitioning from the training phase to the testing phase, the overall performance of the LSTM model remains relatively consistent across both phases. This consistency in performance underscores the reliability of the LSTM model in providing predictions that closely approximate actual monitored results, even in unseen scenarios.

Figure 8 provides valuable insights into the dynamics of the LSTM training process, particularly focusing on the evolution of performance metrics such as RMSE and Loss across different numbers of iterations. **Figure 8(a)** illustrates the relationship between RMSE and the number of iterations, demonstrating a consistent decreasing trend as the number of iterations increases. This trend suggests that increasing the number of iterations during training leads to a progressive improvement in the accuracy and precision of the LSTM model's predictions. Similarly, **Figure 8(b)** showcases the relationship between Loss and the number of iterations, revealing a corresponding downward trend. The reduction in Loss signifies the model's ability to minimize errors and discrepancies between predicted and actual values, thereby preserving the accuracy and fidelity of its predictions.

The pronounced decrease in both RMSE and Loss before reaching 200 iterations underscores the significant impact of early training epochs on enhancing the accuracy and performance of the LSTM model. During these initial iterations, the model rapidly learns and adapts to the underlying patterns and

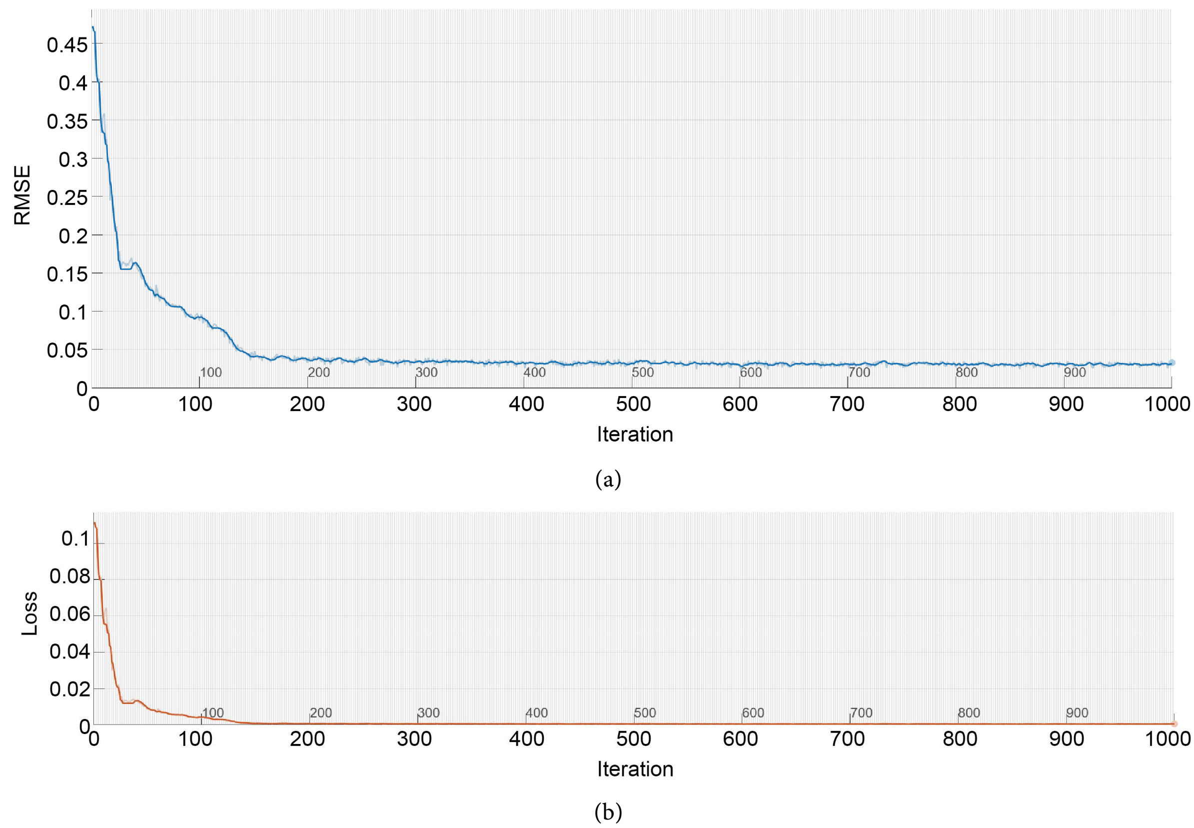

Figure 8. Results of training progress. (a) Result of RMSE; (b) Result of Loss.

dynamics of the input data, resulting in substantial improvements in predictive accuracy. However, beyond the 200th iteration, the rate of improvement in both RMSE and Loss appears to diminish, with no significant differences observed in performance metrics. This stabilization phenomenon suggests that the LSTM model has reached a point of diminishing returns, where additional iterations yield marginal improvements in predictive accuracy.

Table 2 provides a comprehensive overview of the error indices associated with the LSTM model's predictions, specifically focusing on three key metrics: R^2 (Coefficient of Determination), MAE (Mean Absolute Error), and MBE (Mean Bias Error). These error indices play a crucial role in quantifying the accuracy, precision, and bias of the LSTM model's predictions, offering valuable insights into its overall performance across different evaluation criteria.

R^2 is calculated as the square of the correlation coefficient (R) between the observed values of the dependent variable and the values predicted by the regression model. Mathematically, it is expressed as:

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} \tag{12}$$

where, SS_{res} is the sum of squares of the residuals (the differences between the observed and predicted values), and SS_{tot} is the total sum of squares, which measures the total variance in the dependent variable.

Table 2. Error index.

R^2	Training section	0.98785
	Testing section	0.99536
MAE	Training section	2.1875
	Testing section	2.4686
MBE	Training section	−0.0082976
	Testing section	−0.17534

R^2 serves as a measure of the proportion of variance in the observed data that is predictable from the input data, providing an indication of the model's ability to explain and capture the underlying patterns and dynamics of elevator traffic dynamics. A higher R^2 value signifies a stronger correlation between predicted and observed values, indicating a more accurate and reliable predictive model.

The analysis presented in **Table 2** unveils the remarkable accuracy and precision achieved by the LSTM model in predicting elevator traffic dynamics, as evidenced by the high values of the R^2 coefficient of determination. Specifically, the R^2 value of 0.98785 for the training section and 0.99536 for the testing section underscore the robust predictive capabilities of the LSTM model across both training and testing datasets.

Of particular interest is the observation that the R^2 value for the testing section is slightly higher than that of the training section. This intriguing finding suggests that the LSTM model performs exceptionally well when extrapolating learned patterns to unseen data points, outperforming its performance on the training dataset. This phenomenon highlights the robustness and generalization capabilities of the LSTM model, which are critical for its effectiveness in real-world applications.

On the other hand, MAE (Mean Absolute Error) quantifies the average magnitude of errors between predicted and observed values, providing a straight forward measure of prediction accuracy as the equation shows below:

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n} \left| y_i - \hat{y}_i \right|}{n} \tag{13}$$

where y represents the actual data, while $\hat{y}$ represents the predicted data.

Based on the calculation, lower MAE values indicate a closer alignment between predicted and observed values, signifying a higher degree of accuracy and precision in the LSTM model's predictions.

The analysis also presented in **Table 2** reveals crucial insights into the MAE values associated with the LSTM model's predictions for elevator traffic dynamics. Specifically, the MAE value of 2.1875 observed in the training section and 2.4686 in the testing section shed light on the accuracy and precision of the model's predictions across different datasets.

In the context of this research, the training section exhibits a notably lower

MAE value compared to the testing section. This discrepancy suggests that the LSTM model achieves a higher degree of accuracy and precision in predicting elevator traffic dynamics when trained on a specific subset of data. On the other hand, the slightly higher MAE value observed in the testing section suggests that the LSTM model may encounter challenges or limitations when extrapolating learned patterns to unseen data points. Despite this, the MAE values for both sections remain relatively low, indicating that the LSTM model performs admirably in predicting elevator traffic dynamics across diverse datasets.

MBE (Mean Bias Error) measures the average tendency of the model's predictions to overestimate or underestimate the observed values, offering insights into the presence of bias in the model's predictions as the equation shows below:

$$\text{MBE} = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right) \tag{14}$$

where y represents the actual data, while $\hat{y}$ represents the predicted data.

According to equation (14), an MBE value close to zero indicates minimal bias in the model's predictions, while positive and negative values suggest a tendency to overestimate and underestimate, respectively.

The MBE values provided in this research offer crucial insights into the accuracy and bias of the LSTM model's predictions for elevator traffic dynamics. Specifically, the MBE value of −0.0082976 observed in the training section and −0.17534 in the testing section shed light on the presence of biases in the model's predictions across different datasets.

In the context of this research, the training section exhibits a notably smaller MBE value compared to the testing section. This discrepancy suggests that the LSTM model demonstrates minimal bias in its predictions when trained on a specific subset of data. The slightly higher MBE value observed in the testing section indicates that the LSTM model may encounter biases or deviations from the actual observed values when extrapolating learned patterns to unseen data points. Despite this, the MBE values for both sections remain relatively small, indicating that the LSTM model performs well in minimizing biases and accurately predicting elevator traffic dynamics across diverse datasets.

3.3. Elevator Traffic Analysis

Figure 9 offers a comprehensive visual representation of the comparison between actual monitored data and the corresponding predictions generated by the LSTM model across both the training and testing sections. The graphs depicted in **Figure 9** serve as compelling visual evidence of the robustness and accuracy of the LSTM predictor in analyzing elevator traffic dynamics.

Upon examination of **Figure 9**, it becomes evident that the graphs illustrating actual monitored data and LSTM-predicted data exhibit a striking degree of consistency. This deep consistency between the two datasets underscores the LSTM model's remarkable ability to accurately capture and forecast elevator traffic patterns and behaviors.

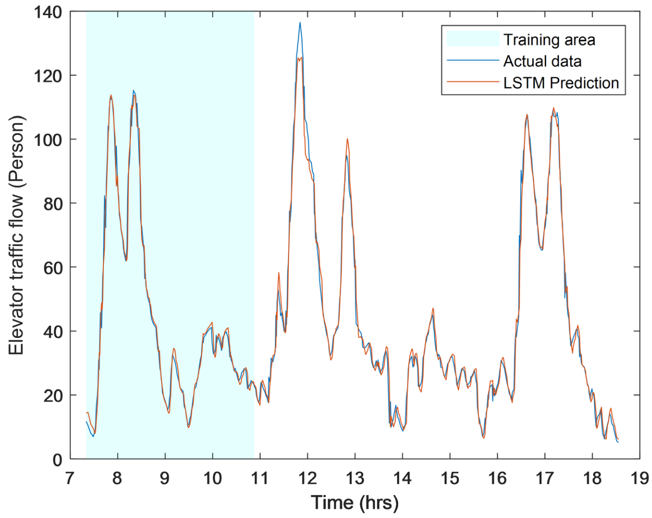

Figure 9. Comparison of the elevator traffic flow.

Moreover, the accuracy of the LSTM predictor extends beyond the confines of the training section to encompass the lunch rush and end-of-day rush periods in the testing area. This observation highlights the model's capacity to generalize learned patterns to unseen data points, thereby demonstrating its efficacy in predicting elevator traffic dynamics across diverse scenarios and time intervals.

Table 3 offers a comprehensive comparison of the maximum traffic volumes observed during the morning rush, noon rush, and end-of-day rush periods, as derived from both actual monitored data and predictions generated by the LSTM model.

Upon scrutiny of **Table 3**, it becomes evident that the LSTM model exhibits a high level of accuracy in predicting traffic volumes during the morning rush and end-of-day rush periods, with a discrepancy rate of merely 1% between the actual monitored data and LSTM-predicted data. This close alignment underscores the robust predictive capabilities of the LSTM model in capturing and forecasting elevator traffic patterns during peak traffic periods.

Conversely, the lunch rush period presents a slightly higher discrepancy rate of 8% between actual monitored data and LSTM-predicted data. This variance suggests a comparatively lower level of accuracy in the LSTM model's predictions for the lunch rush, as evidenced by the higher deviation in traffic volumes between the two datasets. Despite this, the LSTM model still demonstrates a reasonable level of accuracy in analyzing elevator traffic dynamics, albeit with a slightly higher margin of error during the lunch rush period.

Figure 9 visually corroborates the findings presented in **Table 3**, depicting slightly lower passenger numbers predicted by the LSTM model compared to actual monitored data during the lunch rush period. However, the overall trend depicted in **Figure 9** underscores the consistency and accuracy of the LSTM predictor in analyzing elevator traffic dynamics across different time intervals and traffic patterns, despite minor discrepancies between actual and predicted data.

Table 3. Elevator traffic rush.

Types	6:30 - 9:00 (Person)	11:00 - 13:30 (Person)	16:00 - 18:00 (Person)
Actual data	115	137	109
LSTM prediction	114	126	110
Difference rate	1%	8%	1%

Through an analysis of both **Table 3** and **Figure 9**, gain valuable insights into the strengths and limitations of the LSTM model in predicting elevator traffic dynamics. By leveraging these insights, designers can implement targeted strategies to optimize elevator operations, minimize congestion, and enhance passenger experience in elevators as the typical vertical transport tools in urban environments.

4. Conclusions

This research under discussion takes advantage of the capabilities of deep learning, specifically LSTM (Long Short-Term Memory) models based on RNN (Recurrent Neural Network), to analyze and predict elevator flow data in typical office buildings. By applying advanced deep learning techniques to elevator traffic analysis, the study aims to unlock new insights into the dynamics of elevator flow and provide valuable guidance for optimizing elevator group control technology.

The discussion of results in this study evaluates the performance of LSTM across both training and testing phases, emphasizing its accuracy and superiority over traditional methods. The comparison of results accentuates the effectiveness of LSTM, particularly evident in the lower RMSE (Root Mean Square Error) values achieved during both the training and testing processes. The RMSE values of 3.3006 for training and 3.7168 for testing underscore the precision and reliability of LSTM in predicting elevator traffic dynamics.

Furthermore, the study contrasts LSTM with the conventional approach of LS-SVMs (Least Squares Support Vector Machines), as demonstrated by Fei Luo *et al.* [1]. By leveraging LSTM, the research showcases its advantages over LS-SVMs, highlighting its superior performance in analyzing elevator traffic data. This comparison elucidates the enhanced accuracy and efficiency offered by LSTM in capturing complex patterns and dynamics inherent in elevator flow data.

Moreover, the evaluation extends to error indices such as R^2, MAE, and MBE, providing a comprehensive analysis of LSTM's accuracy across both training and testing sections. These error indices offer detailed insights into the predictive capabilities of LSTM, further reinforcing its effectiveness in accurately forecasting elevator traffic dynamics.

The findings of this research hold considerable promise as a valuable reference for elevator traffic analysis, offering insights that can inform and guide future studies and practical applications in the field. The findings in this research are poised to catalyze innovation in elevator traffic management and provide the approach for the development of intelligent control systems that optimize energy consumption while ensuring smooth and efficient vertical transport operations. By leveraging the insights gleaned from LSTM analysis, the elevator group control system can implement data-driven strategies to optimize elevator usage, reduce wait times, and enhance the overall passenger experience within high-rise buildings.

Acknowledgements

The research described in this paper was financially supported by Shanghai HaXell elevator and performed at Kyungpook National University.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

[1] Luo, F., Xu, Y.G. and Cao, J.Z. (2005) Elevator Traffic Flow Prediction with Least Squares Support Vector Machines. 2005 *International Conference on Machine Learning and Cybernetics*, Guangzhou, 18-21 August 2005, 4266-4270.

[2] Pan, Z.F., Luo, F. and Xu, Y.G. (2007) Elevator Traffic Flow Model Based on Dynamic Passenger Distribution. 2007 *IEEE International Conference on Control and Automation*, Guangzhou, 30 May 2007-1 June 2007, 2386-2390.

[3] Hammoudeh, A., Al-Sharif, L. and Al-Shabi, M. (2019) A Benchmark and Real-Time Estimator for the Passenger Arrival Rate to Elevator System. *Building Services Engineering Research and Technology*, **40**, 135-150. https://doi.org/10.1177/0143624418813434

[4] Doğan, E. (2020) Analysis of the Relationship between LSTM Network Traffic Flow Prediction Performance and Statistical Characteristics of Standard and Nonstandard Data. *Journal of Forecasting*, **39**, 1213-1228. https://doi.org/10.1002/for.2683

[5] Lu, H.P. and Yang, F. (2018) A Network Traffic Prediction Model Based on Wavelet Transformation and LSTM Network. 2018 *IEEE* 9*th International Conference on Software Engineering and Service Science*, Beijing, 23-25 November 2018, 1-4. https://doi.org/10.1109/ICSESS.2018.8663884

[6] Bi, J., Zhang, X., Yuan, H.T., Zhang, J. and Zhou, M.C. (2022) A Hybrid Prediction Method for Realistic Network Traffic With Temporal Convolutional Network and LSTM. *IEEE Transactions on Automation Science and Engineering*, **19**, 1869-1879. https://doi.org/10.1109/TASE.2021.3077537

[7] Vinayakumar, R., Soman, K.P. and Poornachandran, P. (2017) Applying Deep Learning Approaches for Network Traffic Prediction. 2017 *International Conference on Advances in Computing, Communications and Informatics*, Udupi, 13-16 September 2017, 2353-2358. https://doi.org/10.1109/ICACCI.2017.8126198

[8] Fu, R., Zhang, Z. and Li, L. (2016) Using LSTM and GRU Neural Network Methods for Traffic Flow Prediction. 2016 31*st Youth Academic Annual Conference of Chi-*

nese Association of Automation, Wuhan, 11-13 November 2016, 324-228. https://doi.org/10.1109/YAC.2016.7804912

[9] Chen, J., Xing, H.L., Yang, H. and Xu, L.X. (2019) Network Traffic Prediction Based on LSTM Networks with Genetic Algorithm. *Signal and Information Processing, Networking and Computers*, **550**, 411-419. https://doi.org/10.1007/978-981-13-7123-3_48

[10] Doğan, E. (2020) LSTM Training Set Analysis and Clustering Model Development for Short-Term Traffic Flow Prediction. *Neural Computing and Applications*, **33**, 11175-11188. https://doi.org/10.1007/s00521-020-05564-5

[11] Ranjan, N., Bhandari, S., Zhao, H.P., Kim, H. and Khan, P. (2019) City-Wide Traffic Congestion Prediction Based on CNN, LSTM and Transpose CNN. *IEEE Access*, **8**, 81606-81620. https://doi.org/10.1109/ACCESS.2020.2991462

[12] Abduljabbar, R.L., Dia, H., Tsai, P.W. and Liyanage, S. (2021) Short-Term Traffic Forecasting: An LSTM Network for Spatial-Temporal Speed Prediction. *Future Transportation*, **1**, 21-37. https://doi.org/10.3390/futuretransp1010003

[13] Abduljabbar, R.L., Dia, H. and Tsai, P.W. (2021) Unidirectional and Bidirectional LSTM Models for Short-Term Traffic Prediction. *Journal of Advanced Transportation*, **2021**, Article ID: 5589075. https://doi.org/10.1155/2021/5589075

[14] Mackenzie, J., Roddick, J.F. and Zito, R. (2019) An Evaluation of HTM and LSTM for Short-Term Arterial Traffic Flow Prediction. *IEEE Transactions on Intelligent Transportation Systems*, **20**, 1847-1857. https://doi.org/10.1109/TITS.2018.2843349

[15] Yang, B.L., Sun, S.L., Li, J.Y., Lin, X.X. and Tian, Y. (2019) Traffic Flow Prediction Using LSTM with Feature Enhancement. *Neurocomputing*, **332**, 320-327. https://doi.org/10.1016/j.neucom.2018.12.016