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Gaussian Analysis of the Elevator Traffic under the Typical Office Building

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Abstract: Elevators serve as indispensable transportation systems in contemporary buildings, facilitating vertical mobility for occupants. However, the proliferation of tall buildings has exacerbated traffic congestion issues within elevator systems. A significant number of elevator passengers voice dissatisfaction with prolonged wait times, leading to impatience and frustration. Traditional approaches to address elevator traffic problems include installing additional elevators or implementing group control systems. However, these solutions often fall short due to designers' limited understanding of elevator traffic dynamics. This research seeks to address these challenges by employing Gaussian analysis to comprehensively examine elevator traffic patterns within a typical office building context. By analyzing both actual monitored data and predictions generated by LS-SVMs, the study aims to offer valuable insights into elevator traffic behavior. Additionally, the research endeavors to serve as a valuable resource for ETA (Elevator Traffic Analysis), providing designers with a deeper understanding of elevator traffic dynamics and guiding the development of more effective solutions to alleviate congestion and improve passenger experience within vertical transportation systems. Through this approach, the study contributes to advancements in elevator design and operation, ultimately enhancing the functionality and efficiency of vertical transportation systems in built environments.

Keywords: ETA (Elevator Traffic Analysis); Gaussian Analysis; LS-SVMs; Office Building.

1. Introduction

Gaussian analysis, also referred to as Gaussian curve fitting or Gaussian distribution fitting, is a fundamental mathematical technique employed in various fields to analyze and model datasets exhibiting characteristics of a Gaussian distribution. This method involves adjusting parameters to best match the observed data to the theoretical Gaussian curve. The Gaussian distribution, often synonymous with the normal distribution, is a probability distribution that describes the frequency distribution of a continuous random variable. It is distinguished by its symmetric bell-shaped curve, where the majority of the data points cluster around the mean, with diminishing frequency as they deviate further from the mean. This distribution is widely encountered in nature and in various scientific disciplines due to its prevalence in phenomena such as measurement errors, biological traits, and physical processes. In general, the formula for the Gaussian can be distributed as:

$$f(x)=\frac{1}{\sigma\sqrt{2\pi}}\cdot e^{-\frac{(x-\mu)^2}{2\sigma^2}} \tag{1}$$

where x represents the variable, μ is the mean or average value of the distribution, and σ is the standard deviation, which measures the spread or dispersion of the distribution.

Gaussian fitting is a computational technique pivotal in statistical analysis, involving the determination of parameters μ (mean) and σ (standard deviation) that best capture the characteristics of a dataset conforming to a Gaussian distribution. This optimization process often employs sophisticated algorithms like least squares fitting or maximum likelihood estimation to iteratively refine parameter values until they closely align with the observed data points.

The versatility of Gaussian analysis transcends disciplinary boundaries, finding applications in an array of domains including but not limited to statistics, physics, engineering, finance, and image processing. Referring to *Xiongwei Sun et al.* [1], Gaussian fitting plays a pivotal role in image contrast enhancement. Furthermore, many other researches also emphasize that Gaussian fitting tasks such as edge detection and object recognition, enable computers to interpret and understand visual information for applications ranging from medical imaging to autonomous driving. Thus, Gaussian analysis stands as a cornerstone technique with broad-reaching implications [2], empowering researchers and practitioners across diverse domains to extract valuable insights from complex datasets and phenomena.

In the realm of traffic analysis, Gaussian analysis emerges as a valuable methodology utilized to unravel the intricate dynamics of traffic flow patterns, with particular emphasis placed on its applications within transportation engineering and urban planning domains [3-5]. This analytical approach encompasses the utilization of Gaussian distributions as a framework to model and dissect various parameters inherent to traffic systems. Primarily, Gaussian fitting involves the alignment of Gaussian curves to empirical traffic data, facilitating a comprehensive understanding of crucial metrics such as vehicle speeds, traffic volumes, and other pertinent variables. By employing this methodological approach, researchers can glean invaluable insights into the underlying structure and behavior of traffic networks, thereby informing strategic decision-making processes aimed at enhancing transportation efficiency, mitigating congestion, and fostering sustainable urban development. Consequently, Gaussian analysis emerges as an indispensable tool in the arsenal of traffic analysts, empowering them with mathematical modeling to tackle the multifaceted challenges posed by contemporary transportation systems.

Gaussian analysis, as applied in traffic analysis, is also utilized in ETA (Elevator Traffic Analysis), drawing from previous research. Researchers have focused on using LS-SVMs (Least Squares Support Vector Machines) to analyze elevator traffic, as *Fei Luo et al.* [6] use mean square root errors as a performance index for elevator traffic prediction.

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

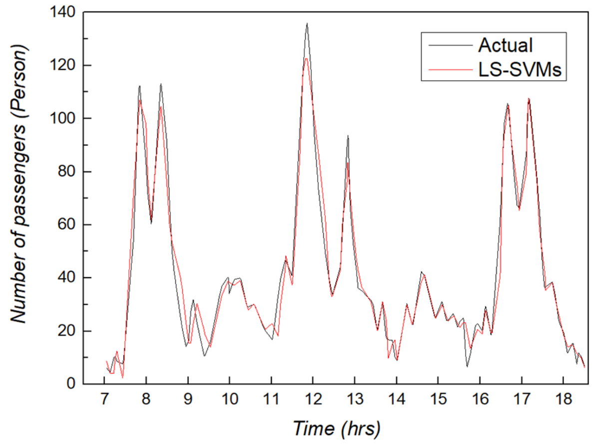
where Y_i is the actual value and Y_{i*} is the predicted value. *Fei Luo et al.* [6] utilized Lagrange multipliers to optimize theoretical calculations and applied LS-SVMs to compute MSE (Mean Square Root Errors) for predicting total, incoming, and outgoing passengers. Their findings closely matched actual data, suggesting LS-SVMs' effectiveness. The results of LS-SVMs are also expected that Gaussian fitting could explain the ETA well.

Moreover, dynamic passenger distribution is also analyzed according to *Zhifeng Pan et al.* [7], who delved into the dynamic passenger distribution, shedding light on the intricate interplay between passenger flows and elevator operations. This investigation not only underscores the significance of understanding temporal variations in passenger demand but also sets the stage for employing Gaussian fitting techniques to dissect and interpret the underlying patterns. Based on Gaussian analysis, researchers anticipate gaining deeper insights into the nuances of both dynamic passenger distribution and ETA, thereby enhancing the understanding of elevator traffic dynamics in complex urban environments. Furthermore, the integration of Gaussian analysis into ETA holds the promise of offering novel perspectives and actionable insights into elevator traffic management, building upon the foundation laid by previous research [8-13] endeavors in this domain. Notably, studies conducted by *Ahmad Hammoudeh et al.* [14] and *Qi Zheng et al.* [15] have contributed seminal insights into the optimization of ETA models, further underscoring the significance of Gaussian fitting methodologies in advancing our knowledge and methodologies for analyzing elevator traffic dynamics.

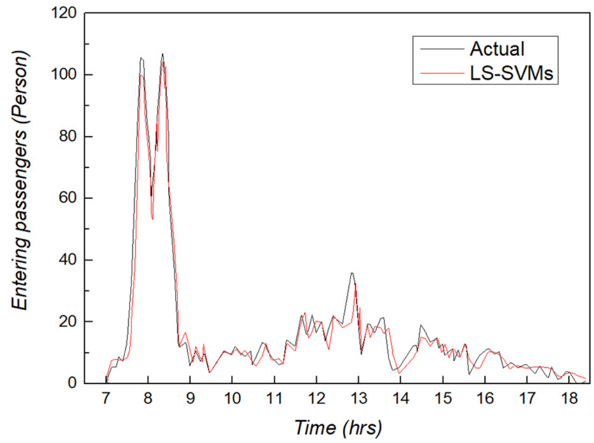
The foundation of this research rests upon the seminal contributions of *Fei Luo et al.* [6], whose prior investigations laid the groundwork for understanding ETA. This study re-analyzes actual monitored data gleaned from typical office buildings during the daytime hours spanning from 6:30 to 18:30. By reanalyzing this empirical dataset, this research endeavors to unearth hidden patterns and insights germane to elevator traffic dynamics within office environments. Leveraging this trove of actual data, this research employs LS-SVMs, to achieve predictive models again. Subsequently, this research employs Gaussian fitting analysis as a major tool to scrutinize the aggregated elevator traffic patterns over the course of a typical workday. This comprehensive analysis encompasses not only the total elevator traffic but also dissects the constituent components, namely the entering and leaving elevator traffic. By juxtaposing the findings derived from Gaussian fitting against the predictions generated by LS-SVMs, this research aims to validate the efficacy of their predictive models while unraveling the underlying dynamics governing elevator traffic within office buildings. Through this iterative process of empirical analysis and computational modeling, the research endeavors to furnish stakeholders within the domain of urban planning and transportation engineering with actionable insights aimed at optimizing elevator operations and enhancing passenger experience.

2. Discussion of the Elevator Traffic

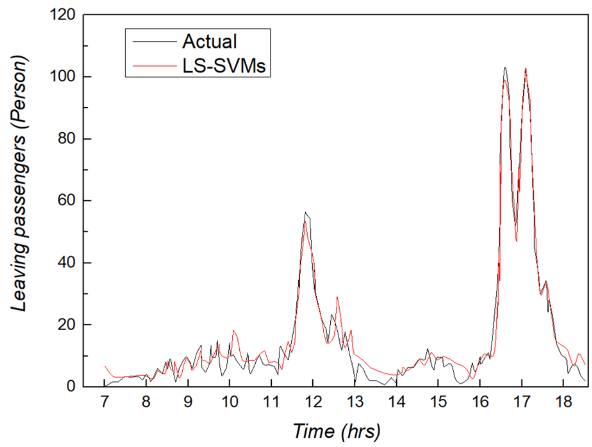
Figure 1 presents graphs displaying both actual monitored data and LS-SVMs predicted data, depicting elevator traffic patterns for one full daytime, entering traffic, and leaving traffic in graphs (a), (b), and (c) respectively.



(a) Elevator traffic per one day



(b) Enter elevator traffic



(c) Leave elevator traffic

Figure 1. Actual elevator traffic and LS-SVMs predictor

Illustrated in Figure 1, graph (a) serves as a visual representation of the fluctuating patterns of elevator traffic observed over the course of a complete daytime cycle. The graph delineates three prominent peaks in elevator traffic, each coinciding with specific time intervals corresponding to the morning rush (6:30 to 9:00), the midday lunch break (11:00 to 13:30), and the end-of-day rush (16:00 to 18:00). These peaks signify periods of heightened elevator traffic activity, reflecting the ebb and flow of human traffic within the building environment. Moreover, a closer examination of the graph reveals an observation: within each primary peak period, there exist two discernible sub-peaks, suggesting a temporal subdivision within the broader peak intervals. This phenomenon underscores the dynamics of elevator traffic, wherein the duration and intensity of peak periods exhibit variability, influenced by factors such as work schedules, lunch breaks, and end-of-day routines. The graphical representation not only offers a comprehensive overview of elevator traffic patterns but also provides valuable insights into the temporal distribution of passenger flows throughout the course of a typical workday. By understanding the elevator traffic per one full daytime, researchers can devise informed strategies aimed at optimizing elevator operations, minimizing congestion, and enhancing overall efficiency within the building environment.

Within the visual framework of Figure 1, graphs (b) and (c) offer a detailed breakdown of elevator traffic patterns observed throughout the entirety of a typical workday. Graph (b) provides a comprehensive portrayal of entering passenger flows over the course of the day, capturing the influx of individuals into the building environment during various time intervals. Conversely, graph (c) offers complementary insights by delineating the departure patterns of passengers, depicting the egress of individuals from the building premises during corresponding time frames. Together, these disaggregated graphs afford a holistic understanding of the temporal distribution of elevator traffic, shedding light on the intricate dynamics governing passenger movements within the building environment. By dissecting elevator traffic into its constituent components—entering and leaving passengers—the graphs facilitate a nuanced analysis of traffic patterns, enabling researchers to identify peak periods, detect trends, and pinpoint potential areas for optimization. Moreover, the visual juxtaposition of entering and leaving passenger flows within the same temporal framework offers valuable insights into the synchronicity of traffic patterns, highlighting potential bottlenecks or congestion points within the vertical transportation system.

Table 1. Elevator traffic rush (Entering passengers)

Types	6:30 – 9:00 (Person)	11:00 – 13:30 (Person)	16:00 – 18:00 (Person)
Actual	107	36	11
LS-SVMs	104	32	10

The visual representation provided by graph (b) in Figure 1 offers valuable insights into the dynamics of entering passenger traffic within the vertical transportation system over the course of a typical workday. During the morning rush hours spanning from 6:30 to 9:00, a pronounced peak in elevator usage is observed, reflective of the influx of individuals commuting to work or arriving at the building premises to commence their daily activities. Delving deeper into the quantitative aspect, Table 1 furnishes empirical data corroborating the observations gleaned from graph (b), with the morning rush period registering the highest number of passengers. According to the actual monitored data, a peak of 107 passengers is recorded during this timeframe, further illustrated by the predictive capabilities of LS-SVMs, which anticipate 104 passengers. This convergence between actual and predictive data underscores the robustness of the analytical framework employed in modeling and forecasting entering passenger traffic patterns. Despite the presence of smaller peaks during the noon and end-of-day rushes, their impact on elevator traffic remains marginal in comparison to the dominant morning rush period. These peaks, while discernible, do not exert a significant influence on overall traffic dynamics, underscoring the resilience and adaptability of the vertical transportation system to accommodate fluctuating passenger demands.

Table 2. Elevator traffic rush (Leaving passengers)

Types	6:30 – 9:00 (Person)	11:00 – 13:30 (Person)	16:00 – 18:00 (Person)
Actual	10	56	103
LS-SVMs	9	54	102

Graph (c) in Figure 1 provides a visual representation of the peak observed in leaving passenger traffic within the vertical transportation system during the end-of-day rush, spanning from 16:00 to 18:00. This spike in elevator traffic is attributed to the exodus of individuals departing from work or vacating the building premises at the conclusion of the workday. Complementing the graphical representation, Table 2 furnishes actual monitored data corroborating the observations gleaned from graph (c), with the end-of-day rush period registering the highest number of departing passengers. According to the actual monitored data, a peak of 103 passengers was recorded during this timeframe, reflected in LS-SVMs, which anticipate 102 passengers. This alignment between actual observations and predictive models reaffirms the reliability and accuracy of the analytical framework employed in forecasting departing passenger traffic patterns. Despite the presence of smaller peaks during the morning and noon rushes in entering passenger traffic, their impact on overall elevator traffic remains negligible.

Table 3. Elevator traffic rush (Full day time)

Types	6:30 – 9:00 (Person)	11:00 – 13:30 (Person)	16:00 – 18:00 (Person)
Actual	113	136	108
LS-SVMs	107	123	107

While graphs (b) and (c) provide insights into the elevator traffic dynamics during the morning and end-of-day rushes, graph (a) in Figure 1 sheds light on the profound influence of the noon rush on elevator usage patterns throughout a complete daytime cycle. Unlike the morning and end-of-day rushes, which primarily reflect commuting patterns, the noon rush is characterized by the departure and return of employees to typical office buildings for lunch. This bi-directional movement of individuals engenders a surge in human flow and elevator traffic, and graph (a) vividly illustrates the magnitude of this phenomenon, with the noon rush exerting a pronounced impact on elevator usage over the entire daytime period. Delving deeper into the quantitative aspect, Table 3 corroborates the observations gleaned from the graph (a) by providing actual monitored data highlighting the peak in elevator traffic during the noon rush. According to the actual monitored data, a peak of 136 passengers was recorded during this timeframe, closely aligned with the predictive estimates derived from LS-SVMs, which anticipate 123 passengers.

3. Gaussian Analysis

3.1. Coding of Gaussian Fitting

This research endeavors to provide a comprehensive overview of the elevator traffic peaks observed within a typical office building environment by leveraging Gaussian analysis techniques. By systematically summarizing the temporal distribution and intensity of elevator usage during key peak periods such as the morning rush, noon rush, and end-of-day rush, researchers aim to unravel the underlying patterns and dynamics governing passenger flow within vertical transportation systems. Gaussian analysis serves as a powerful analytical approach in this endeavor, offering a robust framework for dissecting complex data sets and discerning underlying trends. Through Gaussian analysis, researchers anticipate gaining valuable insights into the intricacies of elevator traffic dynamics, allowing for an understanding of the factors influencing passenger flow patterns and congestion within the building environment. Moreover, Gaussian analysis holds the potential to shed light on additional elevator traffic issues beyond the scope of the typical office building peak periods and provide the way for a more comprehensive and holistic approach to elevator traffic management and optimization. By elucidating the multifaceted nature of elevator traffic dynamics, researchers can devise targeted interventions aimed at enhancing operational efficiency, minimizing congestion, and improving overall passenger experience within the buildings.

```
function [fitresult, gof] = createFit(Time_hrs, Original_Data)
%CREATEFIT(TIME_HRS,ORIGINAL_DATA)
%  Create a fit.
%
%  Data for 'Gaussian Analysis' fit:
%      X Input: Time_hrs
%      Y Output: Original_Data
%  Output:
%      fitresult : a fit object representing the fit.
%      gof : structure with goodness-of fit info.
%
%  See also FIT, CFIT, SFIT.

%  Auto-generated by MATLAB on 12-Apr-2024 19:12:42


%% Fit: 'Gaussian Analysis'.
[xData, yData] = prepareCurveData( Time_hrs, Original_Data );

% Set up fittype and options.
ft = fittype( 'gauss4' );
opts = fitoptions( 'Method', 'NonlinearLeastSquares' );
opts.Display = 'Off';
opts.Lower = [-Inf -Inf 0 -Inf -Inf 0 -Inf -Inf 0 -Inf -Inf 0];
opts.StartPoint = [135.972  11.8528  0.384834347910326  113.135
8.3532   0.835460689595879   107.763   17.1581   0.478806296240343
93.4956660551481 12.8366 0.461278958050749];

% Fit model to data.
[fitresult, gof] = fit( xData, yData, ft, opts );

% Plot fit with data.
figure( 'Name', 'Gaussian Analysis' );
h = plot( fitresult, xData, yData );
legend( h, 'Original_Data vs. Time_hrs', 'Gaussian Analysis',
'Location', 'NorthEast', 'Interpreter', 'none' );
% Label axes
xlabel( 'Time_hrs', 'Interpreter', 'none' );
ylabel( 'Original_Data', 'Interpreter', 'none' );
grid on
```

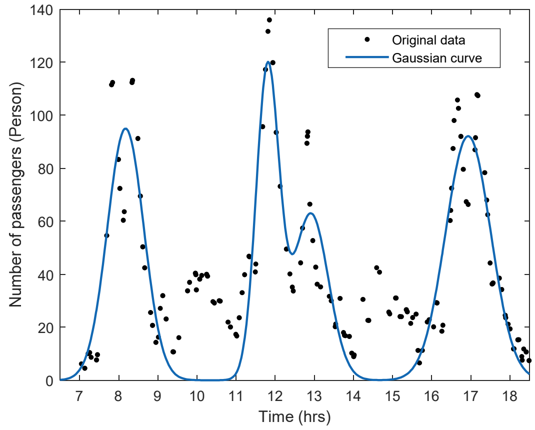
Figure 2. Code of Gaussian analysis on MATLAB

This research employs the approach to Gaussian analysis, necessitating the preparation of two distinct sets of data: one capturing the temporal evolution of elevator traffic (time series data) and the other quantifying the number of passengers flowing through the elevator system. These data sets serve as the foundation for conducting Gaussian analysis, offering insights into both the temporal distribution and the intensity of elevator usage patterns. Leveraging the computational capabilities of MATLAB, utilize curve-fitting techniques to analyze the prepared data sets and derive Gaussian distributions that best characterize the observed patterns. This iterative process involves refining parameters to optimize the fit between the theoretical Gaussian curves and the actual monitored data and LS-SWMs predictor data points, thereby facilitating a comprehensive understanding of elevator traffic dynamics. Figure 2 visually depicts the details of this analytical process, showcasing the specific code of Gaussian analysis through MATLAB.

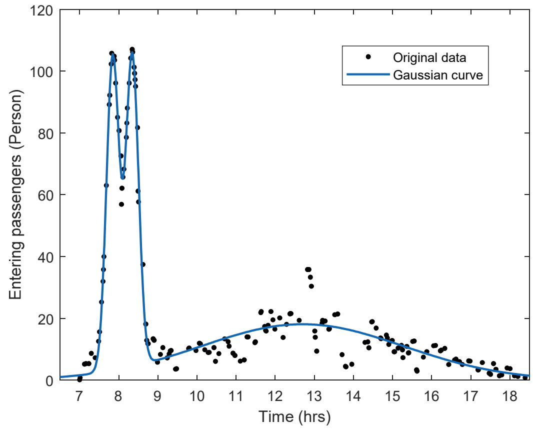
The MATLAB code presented in this research offers a versatile framework for conducting Gaussian analysis tailored to the specific requirements of different elevator traffic analyses. This adaptability is facilitated by the ability to adjust the number of terms utilized in the Gaussian analysis, allowing researchers to customize the analytical approach to suit diverse scenarios and datasets. By altering the 'gauss' parameter within the fittype function, users can specify the number of Gaussian functions employed in the analysis, thereby accommodating variations in elevator traffic patterns and dynamics. This level of customization is invaluable in addressing the inherent complexities of elevator traffic within different contexts, ranging from high-traffic urban environments to low-traffic residential buildings. Researchers can experiment with different configurations of Gaussian terms to capture varying degrees of complexity in elevator traffic patterns, facilitating a nuanced understanding of factors influencing passenger flow dynamics. This flexibility ensures that the analytical framework remains adaptable and responsive to evolving research needs and objectives, empowering researchers to derive meaningful insights from elevator traffic data and inform evidence-based decision-making processes. Through the iterative refinement of Gaussian analysis parameters, researchers can gain deeper insights into the underlying dynamics governing elevator traffic and devise targeted interventions aimed at optimizing system performance and enhancing passenger experience.

3.2. Discussion of Gaussian Fitting Results

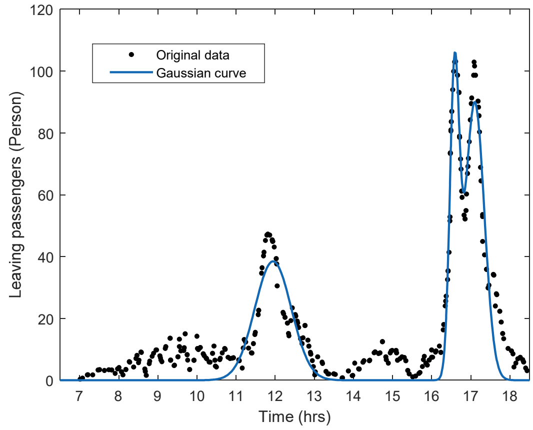
Figure 3 serves as a visual representation of the Gaussian fitting curves generated through MATLAB, offering insights into the temporal distribution of elevator traffic peaks observed over the course of a full daytime cycle. The curves in graphs (a), (b), and (c) reveal the presence of distinct peaks in elevator traffic, each corresponding to a term within the analytical Gaussian function described by equations (3), (4), and (5). Within this analytical framework, parameters ζ, α, and β play pivotal roles in shaping the characteristics of the Gaussian curves, allowing researchers to manipulate peak height, location, and duration. By adjusting these parameters, researchers can modulate the shape and amplitude of the Gaussian curves to accurately capture the dynamics of elevator traffic patterns. Specifically, the peaks of the Gaussian curves signify periods of heightened elevator activity, with their positions indicating the timing of peak traffic occurrences throughout the day. Meanwhile, the length of the wave valleys between peaks provides insights into the duration of elevated traffic levels, facilitating the understanding of passenger flow dynamics within the building environment.



(a) Elevator traffic per one day



(b) Enter elevator traffic



(c) Leave elevator traffic

Figure 3. Gaussian analysis of ETA

Graph (a) elucidates the temporal distribution of elevator traffic peaks through Gaussian curves, revealing four distinct peaks corresponding to different rush hour periods within a full daytime cycle. The first peak signifies the morning rush, symbolizing the surge in elevator usage as individuals arrive at work. The second and third peaks represent the noon rush, reflecting the departure for lunch and return to work, while the fourth peak denotes the end-of-day rush as individuals leave work. This temporal distribution is further corroborated by actual monitored data in Figure 1, referring to the Gaussian fitting function (3) which highlights the highest number of passengers during the noon rush (ζ=116.9), followed by the morning (ζ=95.01) and end-of-day rushes (ζ=92.11) sequentially.

$$\sum_{x=6.5}^{x=18.5} f(x) = \zeta_1 \cdot e^{-\left(\frac{x-\alpha_1}{\beta_1}\right)^2} + \zeta_2 \cdot e^{-\left(\frac{x-\alpha_2}{\beta_2}\right)^2} + \zeta_3 \cdot e^{-\left(\frac{x-\alpha_3}{\beta_3}\right)^2} + \zeta_4 \cdot e^{-\left(\frac{x-\alpha_4}{\beta_4}\right)^2} \tag{3}$$

ζ_1 = 116.9 (97.41, 136.4) / ζ_2 = 95.01 (79.59, 110.4)
ζ_3 = 92.11 (79.99, 104.2) / ζ_4 = 62.92 (48.97, 76.87)
α_1 = 11.81 (11.72, 11.89) / α_2 = 8.176 (8.085, 8.267)
α_3 = 16.93 (16.85, 17.02) / α_4 = 12.91 (12.7, 13.12)
β_1 = 0.4137 (0.3046, 0.5228) / β_2 = 0.6589 (0.5329, 0.7848)
β_3 = 0.8161 (0.6894, 0.9427) / β_4 = 0.6373 (0.3708, 0.9039)

The Gaussian fitting function (3) provides additional insights into these traffic patterns, with ζ values serving as indicators of peak heights. The noon rush, characterized by its unique departure and return dynamics for lunch breaks, exhibits two distinct peaks in both graphs and the Gaussian function (ζ_{noon_1}=116.9 / ζ_{noon_2}=62.92). The presence of two peaks is reflected in the Gaussian curves, with the respective ζ values representing the peak heights for each sub-period of the noon rush.

$$\sum_{x=6.5}^{x=18.5} f(x) = \zeta_1 \cdot e^{-\left(\frac{x-\alpha_1}{\beta_1}\right)^2} + \zeta_2 \cdot e^{-\left(\frac{x-\alpha_2}{\beta_2}\right)^2} + \zeta_3 \cdot e^{-\left(\frac{x-\alpha_3}{\beta_3}\right)^2} \tag{4}$$

ζ_1 = 100.9 (97.26, 104.4) / ζ_2 = 101.5 (97.65, 105.3)
ζ_3 = 18.12 (16.69, 19.56)
α_1 = 8.345 (8.335, 8.355) / α_2 = 7.847 (7.836, 7.858)
α_3 = 12.7 (12.45, 12.94)
β_1 = 0.2292 (0.2126, 0.2458) / β_2 = 0.2264 (0.2121, 0.2407)
β_3 = 3.668 (3.273, 4.063)

$$\sum_{x=6.5}^{x=18.5} f(x) = \zeta_1 \cdot e^{-\left(\frac{x-\alpha_1}{\beta_1}\right)^2} + \zeta_2 \cdot e^{-\left(\frac{x-\alpha_2}{\beta_2}\right)^2} + \zeta_3 \cdot e^{-\left(\frac{x-\alpha_3}{\beta_3}\right)^2} \tag{5}$$

ζ_1 = 95.8 (87.99, 103.6) / ζ_2 = 89.98 (85.32, 94.63)
ζ_3 = 38.46 (34.56, 42.36)
α_1 = 16.58 (16.57, 16.59) / α_2 = 17.1 (17.08, 17.12)
α_3 = 11.95 (11.89, 12)
β_1 = 0.1688 (0.1537, 0.184) / β_2 = 0.3482 (0.3133, 0.3831)
β_3 = 0.6589 (0.5815, 0.7362)

Graphs (b) and (c) serve as visual representations of elevator traffic dynamics for entering and leaving passengers throughout a full daytime cycle. In graph (b), three distinct peaks emerge, each reflecting variations in entering passenger flow. The morning rush is characterized by two prominent peaks, indicative of heightened elevator activity as individuals arrive at work. Meanwhile, the noon rush exhibits a softer peak, likely attributed to individuals leaving for lunch breaks and returning to work. The Gaussian fitting function (4) further elucidates these observations, revealing ζ values of 100.9 and 101.5 for the two main peaks during the morning rush, indicative of their respective peak heights. Conversely, the noon rush entering passenger peak is characterized by a lower ζ value of 18.12, reflecting its comparatively softer intensity.

Conversely, in the graph (c), the temporal distribution of elevator traffic peaks for leaving passengers is depicted, highlighting three distinct peaks corresponding to different rush hour periods. The end-of-day rush is characterized by two main peaks, reflecting the heightened activity as individuals leave work. Additionally, a softer peak is observed during the noon rush, likely attributed to individuals leaving for lunch. The Gaussian fitting function (5) further elucidates these observations, revealing ζ values of 95.8 and 89.98 for the two main peaks during the end-of-day rush, indicative of their respective peak heights. Conversely, the noon rush peak for leaving passengers is characterized by a lower ζ value of 38.46, reflecting its comparatively softer intensity compared to the end-of-day rush peaks.

3.3. Goodness of Fit

Assessing the quality of Gaussian curve fitting is crucial for ensuring the accuracy and reliability of the analytical results. In Table 4, various metrics, including SSE (Sum of Squares Error), R^2 (Coefficient of Determination), Adjusted R^2 (Adjusted Coefficient of Determination), and RMSE (Root Mean Square Error), are utilized to gauge the goodness of fit for each Gaussian curve. A lower SSE indicates a better fit between the curve and the data points, while higher R^2 and adjusted R^2 values signify a stronger correlation between the predicted and actual values. Additionally, a lower RMSE indicates smaller deviations between predicted and observed values, implying higher accuracy in the curve-fitting process. By comparing these metrics across different Gaussian curves, researchers can identify the most suitable model that accurately captures the underlying patterns in elevator traffic dynamics.

Table 4. Goodness of fit

Types	Full day	Enter	Left
SSE	55090	3173	16460
RMSE	19.91	4.467	7.707
R^2	0.6345	0.9786	0.9195
Adjusted R^2	0.6056	0.9776	0.9172

Table 4 provides the results of the SSE (Sum of Squares Error) to quantify the discrepancies between each different Gaussian fitting curve, and the sum of squares due to the error of SSE can be calculated as the equation (6) below:

$$SSE = \sum_{i=1}^{n} w_i (y_i - \hat{y}_i)^2 \qquad (6)$$

The SSE (Sum of Squares Error) serves as a crucial metric for evaluating the accuracy of Gaussian curve fitting in representing elevator traffic patterns. A lower SSE value signifies a tighter fit between the Gaussian curve and the observed data points, indicating higher precision in modeling elevator traffic dynamics.

The analysis in Table 4 reveals that the elevator traffic for one full daytime exhibits the largest SSE value, suggesting a higher degree of variability and complexity in this scenario. This could be attributed to the diverse range of activities and fluctuations in passenger flow throughout the entire workday. Conversely, the SSE for leaving passenger traffic ranks below that of one full daytime traffic, indicating a relatively better fit for the leaving traffic scenario. Interestingly, the entering passenger flow demonstrates the smallest SSE value, indicating the best fit among the analyzed scenarios. This suggests that the Gaussian analysis effectively captures the patterns and trends inherent in entering passenger flow data, outperforming its fitting for leaving passenger flow and overall daytime traffic.

MSE (Mean Square Error) also plays a pivotal role in assessing the precision of Gaussian curve fitting in modeling elevator traffic dynamics, and the mean squared error of MSE can be calculated as the equation (7) below:

$$MSE = \frac{SSE}{n} = \frac{1}{n} \cdot \sum_{i=1}^{n} w_i (y_i - \hat{y}_i)^2 \qquad (7)$$

Equation (7) serves as a pivotal tool for understanding the relationship between SSE and MSE, fundamental metrics used to evaluate the accuracy of Gaussian curve fitting. By dividing SSE by the number of data points (n), MSE is derived, providing a normalized measure of the error between predicted and observed values. Due to the relationship between SSE and MSE, similar to SSE, a lower MSE value signifies a tighter fit between the Gaussian curve and the observed data points. Essentially, a lower MSE suggests that the predicted values are, on average, closer to the actual observations, indicating higher precision in modeling elevator traffic dynamics.

Moreover, rooting the value of MSE, the value of RMSE can be calculated as the equation (8) shows below:

$$RMSE = \sqrt{MSE} = \sqrt{\frac{SSE}{n}} = \sqrt{\frac{1}{n} \cdot \sum_{i=1}^{n} w_i (y_i - \hat{y}_i)^2} \qquad (8)$$

Analysis of Table 4 reveals notable discrepancies in the accuracy of Gaussian curve fitting across different elevator traffic scenarios. The entering passenger flow stands out for its remarkably low RMSE value of 4.467, indicating a high degree of precision in modeling elevator traffic dynamics. This suggests that the Gaussian three-term function effectively captures the underlying patterns and trends observed in entering passenger flow data, resulting in a highly accurate representation.

Conversely, the leaving passenger flow exhibits a slightly higher RMSE value of 7.707, indicating a somewhat less precise fitting compared to the entering passenger flow based on the same Gaussian three-term function.

Of note, the full daytime elevator traffic scenario demonstrates the least accurate fitting, as evidenced by the highest RMSE value of 19.91. This suggests that the Gaussian four-term model struggles to accurately represent the complex and dynamic nature of elevator traffic patterns observed throughout an entire workday. Factors such as varying traffic intensities, peak periods, and human behavior dynamics may contribute to the higher level of error in this situation.

The relationship between SSE and RMSE findings and those of R^2 and Adjusted R^2 metrics sheds light on the effectiveness of Gaussian curve fitting across different elevator traffic scenarios. The entering passenger flow emerges as the most accurately fitted scenario, evident from its highest R^2 value. This signifies a strong correlation between the predicted values and the observed data points, indicating that the Gaussian curve fitting model effectively captures the underlying patterns in entering passenger flow data.

In contrast, the leaving passenger flow demonstrates a relatively lower R^2 value of 0.9195. While still indicating a substantial correlation, this suggests a somewhat weaker fit compared to entering passenger flow.

Notably, the elevator traffic for one full daytime exhibits the lowest R^2 and Adjusted R^2 values. This also suggests that the Gaussian four-term model struggles to accurately represent the complex and dynamic nature of elevator traffic patterns observed throughout an entire workday.

3.4. Summarization of Gaussian Analysis

Across analyzing the Gaussian fitting results in detail, it becomes evident that elevator traffic dynamics can be effectively summarized and modeled using the Gaussian function presented as function (9) shown below:

$$\sum f(x) = \zeta_1 \cdot e^{-\left(\frac{x-\alpha_1}{\beta_1}\right)^2} + \zeta_2 \cdot e^{-\left(\frac{x-\alpha_2}{\beta_2}\right)^2} + \ldots + \zeta_n \cdot e^{-\left(\frac{x-\alpha_n}{\beta n}\right)^2} \quad (9)$$

Where parameters ζ, α, and β play pivotal roles in characterizing these dynamics: ζ signifies peak values, providing information on passenger flow intensity during the morning rush, noon rush, and end-of-day rush. α represents the precise timing of peak elevator usage, while β delineates the duration of each rush period. Moreover, the characteristics of the Gaussian function allow for adjusting the number of terms in function (9), enabling the accommodation of varying numbers of peaks to suit different elevator traffic scenarios.

By mapping the time interval from 6:30 to 18:30 onto the value of x, researchers can analyze elevator traffic patterns throughout a typical workday comprehensively. This approach facilitates a nuanced understanding of peak periods and their temporal distribution. Leveraging function (9), researchers can make informed decisions to optimize elevator operations, manage congestion, and improve passenger experience within built environments.

4. Conclusion

ETA (Elevator Traffic Analysis) plays a crucial role within group control systems, optimizing elevator operations to efficiently manage passenger flow within buildings. This research focuses on elevator traffic dynamics within typical office buildings, recognizing the importance of understanding and improving vertical transportation systems. By employing Gaussian analysis, the research endeavors to develop a comprehensive model that captures the inherent complexities of elevator traffic patterns. The Gaussian model is expected to be a valuable reference for elevator transportation engineering, facilitating informed decision-making processes aimed at enhancing elevator efficiency, reducing congestion, and improving overall passenger experience. Through this endeavor, the study contributes to advancements in elevator traffic analysis methodologies and the assistance for innovation and optimization in vertical transportation systems within built environments.

By examining the performance of LS-SVMs in predicting elevator traffic and comparing it with actual monitored data, this study underscores the effectiveness and rationality of using LS-SVMs as a predictive tool in elevator traffic analysis. Furthermore, the study evaluates the applicability of the Gaussian function in modeling elevator traffic dynamics by comparing results obtained from actual monitored data and LS-SVMs predictions. Through this analysis, the research demonstrates the validity and rationality of utilizing the Gaussian function to characterize elevator traffic patterns in specific building contexts. This approach provides a framework for understanding and analyzing elevator usage dynamics, enabling designers to make informed decisions regarding elevator system design, operation, and optimization.

The Gaussian four-term function in this research may lack the specificity required to accurately model elevator traffic throughout a full workday, particularly regarding the intricacies of entering and leaving passenger flows. However, there is optimism that by adjusting the terms and parameters of the Gaussian function, informed by Equation (9), its efficacy in representing elevator traffic patterns can be significantly improved. This adjustment could involve modifying the number of terms within the function to better align with observed data patterns, as well as fine-tuning parameters such as ζ, α, and β to accurately capture the nuances of elevator usage dynamics.

This research places significant emphasis on leveraging Gaussian analysis techniques to understand and analyze elevator traffic dynamics comprehensively. The findings also distinguish between simple Gaussian functions (Fewer equation terms), which offer a straightforward representation of elevator traffic patterns for easy comprehension, and complex Gaussian functions (More equation terms), which provide a more nuanced and accurate depiction. By comparing these two types of functions, the study aims to provide designers with a range of analytical tools suited to their specific needs and preferences. For instance, simple Gaussian functions may be preferable in scenarios where a broad overview of elevator traffic dynamics is sufficient, while complex Gaussian functions are better suited for situations requiring a detailed and precise understanding.

By offering insights into the strengths and limitations of various Gaussian analysis approaches, the study aims to inform decision-making processes in elevator traffic engineering. Ultimately, the goal is to optimize elevator operations, reduce congestion, and enhance passenger experience within built environments through informed and data-driven strategies.

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