Dynamic optimization of elevators using biometric identification systems

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Abstract: The research focused on developing a real-time monitoring algorithm for elevators in residential towers. The study employed methods, models, and software tools to build intelligent real-time decision-making systems. A model for the elevator setting process was implemented through a Markov decision-making process. The theory of mass service was applied to describe the model of elevator operations. Passenger waiting time patterns at some levels of the towers have been established. A mathematical model for managing passenger flows through the elevators of a high-rise building in real-time using facial recognition identification technology has been developed. In test mode, a face-recognition elevator control system has been installed in 4 elevators. The scientific value of the work resides in the multi-purpose nature of the mathematical optimization model, its simplicity and accuracy. The proposed model allows optimizing numerous elevator systems with a constantly evolving control algorithm tailored to the customer's preferences.

Keywords: lifting facility, Markov process, mathematical model, traffic fluctuations, biometric data, SDG.

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1 Introduction

For many years, an elevator has been an essential appliance in office buildings, public spaces, and apartment buildings that are important for sustainable development goals (SDGs) of city. There are many high-rise buildings in mega-cities worldwide, including Moscow, with over a hundred buildings on 25 floors. It is an element that enhances comfort and a standard without which it is difficult to imagine the operation of people using these facilities. In large multi-story buildings and locations with high transportation requirements between floors, building administrators and owners are required to install more elevators at the facility (Rohatgi et al., 2019). Unfortunately, increasing the number of elevators does not directly improve the system's efficiency in a linear manner (Liu et al., 2020, Wang et al., 2015). The solution to this problem is their logical combination into a single transport module, commonly called a group of lifts (Luo et al., 2020). It is necessary to exchange messages among all group elevators on all orders and calls to ensure appropriate control. Often it may be in the form of broadcasts to any devices connected to the busbar. The issue of accessing elevator call history and elevator passenger biometrics has yet to be resolved. Without this data, an incomplete input data issue exists for each depth control algorithm (Dongmei, 2014; Ghaleb and Oommen, 2020).

An elevator running as a vertical vehicle is autonomous and cannot receive detailed movement information. This significantly reduces the flexibility and efficiency of vertical transport. Primarily during peak hours, the limited physical capacity of the lift with the immediate increase in traffic generates the issue of vertical bottlenecks in large buildings. A technical solution in the form of an end-to-end architecture comprising three aspects is proposed to optimize the operation of the elevators. These are technologies that enable using the Internet of Things (IoT) in a conventional elevator and SDGs (Wang et al., 2015), an agent server to expand the computational capabilities of the elevator, and a new user interface to deliver system intelligence to end-users. This article presents a technological development called Intellevator. This intelligent elevator system enables a passively operated elevator system to be proactive and thoughtful in traffic control to maximize passenger transportation efficiency. This suggestion has been tested on a conventional elevator in an intelligent construction environment. The results of the numerical simulation showed an increase in the effectiveness of the SDGs system. Furthermore, system usability and user interaction were also assessed in a user study.

It is necessary to consider the economic challenges of operating equipment when creating an algorithm that optimizes the order for group elevators and a unique system (Ghaleb and Oommen, 2020; Wang et al., 2015). Usually, the critical task of the algorithm to optimize the operation of a group of elevators is only to reduce the wait time for passengers to perform transportation tasks. It often leads to higher electricity consumption (Yaman and Karakose, 2017). A high number of trips increases wear on the functional parts of the elevator, such as relays, bearings, and other friction elements. The opposite approach aims to conserve energy by improving transportation efficiency and SDGs, which significantly reduces passenger comfort. Another possible solution is to optimize the functioning of the elevators according to the operating profile of the devices on installation sites such as residences, offices, office buildings, hospitals, restaurants, hotels, multi-story buildings, user habits, trends, and history of elevator use (Blakeley et al., 2003). Unfortunately, this method requires advanced and specialized systems that monitor the operation of the lifts and predict the use of a given elevator depending on the history of operations stored in a database. For this purpose, dedicated data archiving systems should be used separately for each elevator. Simulations of advanced algorithms to optimize the elevator movement show the possibility to achieve energy savings of up to 34% with unchanged or even reduced time of transport tasks (Blakeley et al., 2003). That is an essential concept, showing how much reserve must still be used in optimizing the operation of lifting facilities. It becomes beneficial if the application of new solutions does not require a substantial increase in investment costs (Fu and Zhao, 2021). In addition to reducing energy consumption, an optimal number of vehicle movements will result in much lower wear rates on equipment components. Moreover, shortening the duration of transportation tasks will result in greater user satisfaction (Tukia et al., 2018). Due to high capital costs and technical complexity, this solution is usually used in specialized premium buildings. In practice, for example, elevators are controlled by less sophisticated algorithms that do not take into account the nature and purpose of the building and historical information on passenger traffic in buildings (Siikonen, 1993; Sorsa et al., 2018).

There are some elevator control problems in worldwide practice, making it possible to optimize the equipment robot. However, most importantly is to predict the state of the
"elevator - passenger flow" system to select the optimum strategy in real-time. Another important aspect of this problem is to compile a database of profiled passengers to optimize the depth control algorithm. The scientific novelty of our research is the application of biometric passenger profiling using facial recognition or the use of customized magnetic cards. This approach will enhance the "elevator - passenger flow" robot due to the accumulation of statistical information on the passengers in elevators.

An effective method to optimize a passenger or transport network is mass service theory, also known as queue theory (Choi and Kim, 2020). This theory relies on mathematical models and quantitative analysis of service wait processes for the selected equipment. The mathematical description in mass service theory requires a specified mathematical description of a Markov system with a Poisson inflow, exponential service time and a set of service stations, resulting from the previous steps. Markov's mass service systems can be described as individual queries to the system and their arrivals are mutually independent and independent of the service mechanism. The use of Markov processes in queue theory shows the performance of a notification processing system as a system that relies on random events (He and Jiang, 2018). Therefore, the main purpose of this paper based on the theory of mass service is to develop a real-time optimization algorithm for the operation of elevators in multi-storey buildings to minimize the waiting time of elevators.

1.1 Literature review

Global experience in elevator development demonstrates the need for state-of-the-art technology. Thanks to Big Data and the Internet of Things (IoT) technologies, the elevator can be controlled using a mobile application or facial recognition sensors (Wu and Wang, 2018). There is also a facial recognition system where passengers appear upon landing in front of the elevator for the first time. In this case, the elevator automatically recognizes the sides and automatically opens the door. The classical theory describes four models of motion during a typical day in buildings where people work. These patterns depend on whether the main flow rises significantly from the main floor (peak up), descends to the main floor (peak down), both (peak lunch) or not (between floors) (He et al., 2021). In a typical office building, the peak is usually at the beginning of the day, and the peak drop is at the end of the day. The lunchtime peak corresponds to a mid-day break, and the interstitial pattern characterizes a smooth and uniform demand for the rest of the day. Constant changes in passenger movement and cabin occupancy influence the selection of elevators (Ozmen Koca et al., 2018). There are several reasons for thorough traffic analysis in a building prior to programming the dispatching algorithm. First, most of the controller's algorithms are pre-configured and use performance rules applied based on the type of traffic in the building. It means that the EGCS must include some traffic detector. Second, identifying the traffic period in the building is crucial since much of the calculation for estimating passenger AWT, round-trip times, and other performance indicators depend on defining the appropriate peak period (Wang-biao et al., 2019). For example, if peak load situations cannot be identified quickly, long queues may form on the main entrance floor of the building (usually on the first floor), and the passenger waiting times will increase. Long wait times result in dissatisfaction with elevator operations. However, the maximum load mode should not be activated unnecessarily. The rule of returning the elevators directly to the entrance floors will be triggered, leading to long waiting times for passengers on other floors (Cheng et al., 2016).

A Monte Carlo mathematic depth control model is proposed. That model is very accurate. Passengers on different floors are counted with the help of an infra-red sensor. After that, a Monte Carlo algorithm is implemented to optimize the program of elevators (Bapin and Zarikas, 2019). Although this circuit is sensitive to external perturbations and interferences, a genetic algorithm is often used to optimize controller gain (Zhang et al., 2020). Using New York as an example, the results of elevator monitoring show that elevators consume over 1% of the city's power in a year. Moreover, the cost per hour ranges from 0.5% to 3%, depending on the time of day (Hill et al., 2018). Thus, the worldwide practice of using elevators dictates modern methods of monitoring passenger behavior to optimize the "elevator-passenger" system for SDGs (Tukia et al., 2019).

For studying the decision-making process, especially for vehicle passengers, a Markov decision-making model was applied based on random changes in the system condition according to the proposed transition rule (Guan et al., 2020). However, this model also presents the problem of uncertainty in the practical tasks of decision-making. The use of probability theory methods (Mezhennaya and Pugachev, 2018), fuzzy sets (Ashraf et al., 2019), Dempster-Schiefer theory (Chen and Deng, 2018) is widely used in many areas of image recognition, multiple attribute decision making to manage uncertainty.

Combining these methods with the Markov model gives good results in determining the precision of decision making, which can be used to predict the modeling of optimization processes of elevator operation.

1.2 Problem statement

Optimizing elevator control algorithms is an important issue related to passenger transport optimization and economics. The reduction of waiting times and traffic optimization in elevators can be achieved through real-time dynamic simulation of passenger behavior. The primary purpose of this work was to develop a mathematical model for the behavior of the elevator-passenger system to ensure the quality of service to passengers in the lifts of the multi-storey building in real-time. The work aimed to establish the possibility of transferring data with the algorithms for their analysis to an external device shared by many lifting devices and using the Internet to send optimized control data for passenger elevator control systems. In addition to reducing capital and operational costs, this solution will allow registering elevator emergencies and react more quickly to service team malfunctions.

The study aimed to solve the following tasks:

- determining the waiting time for the passengers of the elevator cabin, depending on the floor;
- making a forecast of passenger visits to a particular floor;
- determining the suitability of the mathematical model based on data obtained for elevators with different control systems;
- drawing up theoretical bases for the reading and processing of biometric information in order to determine the destination of passengers presenting a profile.

2 Materials and methods

The research was carried out using the equipment of the Research Center for Food and Chemical Technologies of KubSTU (CKP_3111).

The lift core was written in Python. Event data logging in elevators, which connects passenger IDs obtained through facial recognition, was based on the mass service theory. For establishing a probabilistic model of elevator operation in real-time, a model based on mass service theory has been developed (Tukia et al., 2018).

The Markov process assumes that the system can be in one of two conditions at each moment: a positive state |├ S(0)⟩=|├ +⟩, or a negative state|├ S(0)⟩=|├ -⟩, representing another orientation. The uncertainty is represented by the assignment of an initial probability distribution for these two options, denoted as φ+(0) for plus and φ-(0) for minus, which satisfy the equation φ_+ (0)+φ_- (0)=1.

Therefore, the initial state of the system is determined by the probability distribution matrix as:

$$\varphi(0) = \begin{bmatrix} \varphi_+(0) \\ \varphi_-(0) \end{bmatrix} \tag{1}$$

If the system is started from a positive state, then φ_+ (0)=1; otherwise φ_- (0)=1.

The transition probability matrix T after some time t1 is defined as:

$$T(t_1, 0) = \begin{bmatrix} T_{+,+}(t_1, 0) & T_{+,-}(t_1, 0) \\ T_{-,+}(t_1, 0) & T_{-,-}(t_1, 0) \end{bmatrix}, \tag{2}$$

where, T_(+,-) (t_1,0)T represents the probability of transition from a negative state at time zero to a positive one at time t1 and other relevant processes.

The transition matrix with the initial probability distribution at the starting point gives the updated distribution over the two states at time t1.

$$\varphi(t_1) = T(t_1, 0) \cdot \varphi(0) \tag{3}$$

Thus, knowing the state at time t1, updating the matrix using the transition matrix T(t2,t1) for the period from t1 to t2 is as follows:

$$\varphi(t_2) = T(t_2, t_1) \cdot T(t_1, 0) \cdot \varphi(0). \tag{4}$$

Generally, the transition matrix is assumed to be fixed for many applications. Hence, the transition matrix can be written as T(t), where t is the time moment. The transition matrix is defined as follows:

$$T(t+u) = T(t) \cdot T(u) = T(u) \cdot T(t), \tag{5}$$

Where u is some other period not equal to t.

The following differential equations express the change in the transition matrix and probability distribution over time:

$$\frac{dT(t)}{dt} = K \cdot T(t)$$
$$\frac{d\varphi(t)}{dt} = K \cdot \varphi(t) \tag{6}$$

where K is the intensity matrix. The matrix K must satisfy the following limitations: the non-diagonal elements must be non-negative, but their sum must be zero with a column.

The solutions to differential equations are matrix exponential functions:

$$T(t) = e^{Kt}, \quad \varphi(t) = e^{Kt}\varphi(0) \tag{7}$$

To get the probability of response at different points over time, the measuring matrices are defined as:

$$M_+ = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} \tag{8}$$
$$M_- = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}$$

where M+ and M- are positive and negative state measurement matrices, respectively.

It is assumed that R(t)=+ denotes that the system is in the positive state at time t. Using the matrix L=[1, 1], all states are summed up. Then the probability of observing a positive response at time t is as follows

$$p(R(t) = +) = L \cdot M_+ \cdot T(t) \cdot \varphi(0) \tag{9}$$

If the initial state is known to be positive or negative, the probability is the following:

$$p(R(t) = + | +) = T_{+,+}(t)$$
$$p(R(t) = + | -) = T_{+,-}(t) \tag{10}$$

correspondingly.

If the initial state is unknown, the probability R(t) = + is

$$p(R(t) = + | U) = T_{+,+}(t)\varphi_+(0) + T_{+,-}(t)\varphi_-(0) \tag{11}$$

The discrete states of the system can be presented as follows: S_1 represents an idle state of the elevator on a certain floor, S_i is upward motion, and S_j is downward motion. The process is limited to the states of the system in real-time. All changes of the elevator's states following the model of the mass-service system from state S_i to state S_j occur arbitrarily with intensities λ_{ij}, and the downward motion of the elevator is determined by the intensity μ_{ij}. Thus, the probability that the system is in a particular state S at time t will be defined as p_i. For any time τ, the normalization condition can be written with the sum of probabilities for all states equal to 1:2

$$\sum_{i=1}^{n}(\lambda_i + \mu_i)p_i(\tau) = (\lambda_1 + \mu_1)p_1(\tau) + (\lambda_2 + \mu_2)p_2(\tau) + \ldots + (\lambda_n + \mu_n)p_n(\tau) = 1 \tag{12}$$

In this study, three states of the system (S_0, S_i, and S_j) are defined, so the equation (12) will look as follows:

$$\sum_{i=1}^{3}\lambda_i \cdot p_i(\tau) = \lambda_{01} \cdot p_1(\tau) + \lambda_1 \cdot p_1(\tau) + \lambda_2 \cdot p_2(\tau) = 1 \tag{13}$$

For all modes of upward motion of the elevator cabin, a system of equations based on equation can be written (13)

$$\begin{cases} \lambda_0 p_0 = \mu_0 p_1 \\ \lambda_1 p_1 = \mu_1 p_2 \\ \dots\dots\dots\dots\dots \\ \lambda_{i-1} p_{i-1} = \mu_{i-1} p_i \\ \lambda_{n-1} p_0 = \mu_n p_n \\ p_0 + p_1 + \dots + p_i + \dots + p_n = 1 \end{cases} \quad (14)$$

For all modes of the downward elevator motion, a system of equations based on equation (13) can be written:

$$\begin{cases} \lambda_0 p_0 = \mu_0 p_1 \\ \lambda_1 p_1 = \mu_1 p_2 \\ \dots\dots\dots\dots\dots \\ \lambda_{j-1} p_{i-1} = \mu_{j-1} p_j \\ \lambda_{m-1} p_m = \mu_m p_m \\ p_0 + p_1 + \dots + p_i + \dots + p_m = 1 \end{cases} \quad (15)$$

The joint solution of systems (14) and (15) will allow obtaining the probability of the elevator cabin staying on a particular floor, including the direction of elevator movement.

The computing algorithm was solved using the Euler, Runge-Kutta, or Kremer methods. The probability of the elevator remaining on a certain floor and the direction of its movement can be represented as:

$$p_{i,j} = \frac{\lambda_{i,j}!}{\mu_{i,j}!} \quad (16)$$

2.1 Experimental procedure

For data collection and processing using the developed model, observations were made in residential buildings and business centers using surveillance cameras in the entrance halls and elevators. The experiments were conducted on 50 multi-storey objects located in different neighborhoods of Moscow, with a total number of floors from 26 to 80. Data were collected for one year (2020-2021). The data obtained allowed extracting information on the date, time, and recording of the floor selection during the waiting and moving in the elevator. The number of passengers within the elevator and those waiting upstairs was also recorded.

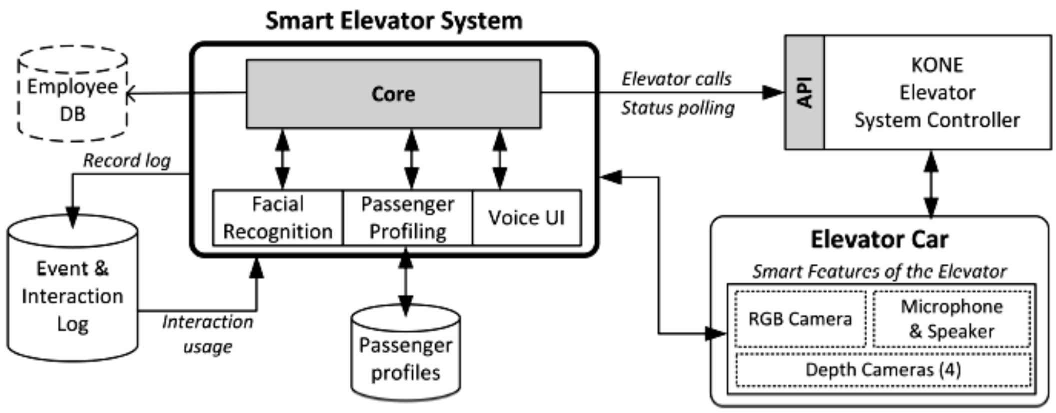
2.2 Statistics

Experimental data were subjected to statistical analysis using Statistica and MS Excell software, according to (MacDonald and Pienaar, 2021).

The statistical reliability of passenger wait time dependency on a given floor and their number was set at $p<0.05$. The Poisson parameter λ was calculated using the equation describing the Poisson distribution. Moreover, *e* is an exponent, i.e., Euler number (e= 2,71828...), and *k!* is a factorial *k* = 0, 1, 2.... The positive values of λ are equal the mathematical hope X and variance computed for a set of experimental data in the Excel environment.

The proposed solution offers significantly higher functionality and efficiency of the optimization algorithm at a very low investment cost for such work. The model of elevator control is shown in Figure 1.

Figure 1 Scheme of elevator control based on artificial intelligence and face recognition system



Another benefit is the possibility of changing the control algorithm of a group of devices and rapidly testing its effect on system performance. The control algorithm can be updated in current solutions if necessary. In addition, it is always required to develop a new software version planned for this microcontroller system, check it in a test environment, upload it separately to each controller with a programmer, and verify its accuracy.

The model accuracy-test involves the construction of the confusion matrix. The confusion matrix of the defect detection results in this work visualizes the model accuracy by comparing the actual and predicted data. The accuracy, precision, sensitivity, specificity and Fscore from confusion matrix are defined as:

Accuracy = (TP + TN)/(TP + FP + FN + TN) (9)

Precision = TP/(TP + FP) (10)

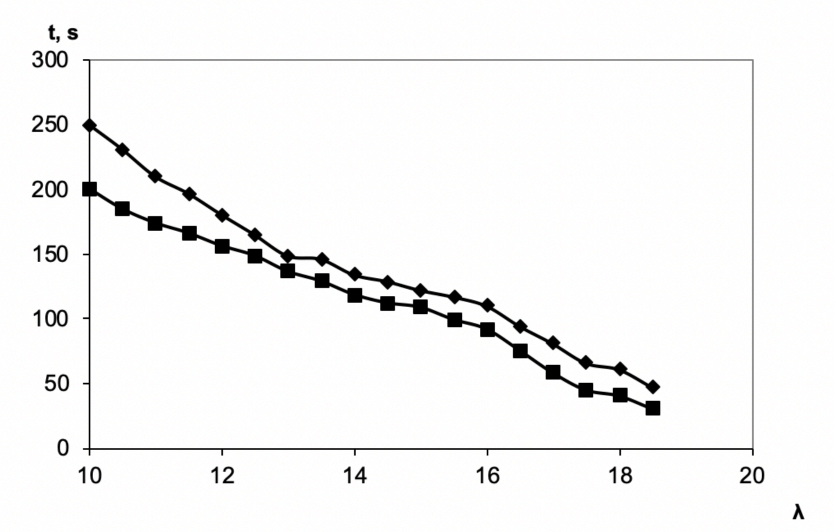
Sensitivity = TP/(TP + FN) (11)

Fscore = 2×TP/(2×TP + FP + FN), (12)

where TP, TN, FP and FN are true positive, true negative, false positive, and false negative, respectively.

3 Results

Figure 2 Average elevator waiting time as a function of traffic, where ■ – data for elevators with facial recognition system; ♦ – data for regular elevators



It follows from Figure 2 that for the high values of the elevator standby time, the divergence of the values represented by the Poisson parameter is lower than that of the common values of the standby time of the lift. Statistical evaluation of the results is presented in Table 1 and Table 2.

Table 1 Results of statistical analysis of experimental and theoretical data of elevator elevators operation

	Observed Value	*Predicted Value*	*Residual*	*Standard Pred. v.*	*Standard Residual*	*Std.Err. Pred.Val*	*Mahalanobis Distance*	*Deleted Residual*	*Cook's Distance*
1	7.00	4.55	2.45	-2.70	10.12	0.28	7.27	-6.91	550.50
2	7.00	4.56	2.44	-2.64	10.08	0.28	6.94	-8.14	732.75
3	8.64	4.58	4.06	-2.50	16.75	0.26	6.25	-22.07	4910.88
4	7.40	4.57	2.83	-2.57	11.69	0.27	6.62	-11.48	1399.94
5	6.00	4.45	1.55	-3.25	6.38	0.33	10.58	-1.71	47.29
6	6.63	4.55	2.08	-2.67	8.58	0.28	7.12	-6.29	448.51
7	7.26	4.65	2.61	-2.09	10.77	0.23	4.35	19.72	2871.99
Minimum	6.00	4.45	1.55	-3.25	6.38	0.23	4.35	-22.07	47.29
Maximum	8.64	4.65	4.06	-2.09	16.75	0.33	10.58	19.72	4910.88
Mean	7.13	4.56	2.57	-2.63	10.62	0.28	7.02	-5.27	1565.98
Median	7.00	4.56	2.45	-2.64	10.12	0.28	6.94	-6.91	732.75

The comparison between the experimental model and the theoretical calculations shows that the model is sufficiently reliable. The difference between the values is an average of 2.5 minutes, and the average error tolerance is 0.28, indicating that using the model reduces the waiting time when optimizing elevator operation.

It should be noted that the predicted values of on-site passenger wait times are relatively consistent for each floor, allowing for stable operation of the equipment.

Table 2 Statistical assessment of the results of the floor selection prediction for elevator passengers

Period of day (24h)	*Prediction accuracy [%]*	*Periodic prediction accuracy [%]*	*Improvement [%]*	χ^2	*t-test*
06 – 11	70.8	72	1.69	0.38	0.016
11 – 15	66.5	72	8.27	0.38	0.015
15 – 19	65.9	69.9	6.06	0.44	0.048
19 – 06	49	61	24.4	0.48	0.109

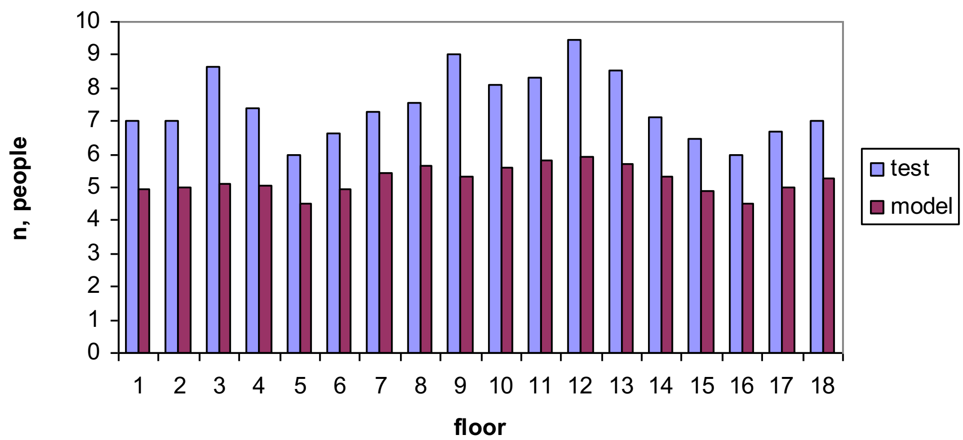
Overall	63.05	68.725	9.00	0.97	-

As seen from Table 2, the forecast accuracy varies depending on the time of day and consequently the elevator traffic load. The highest accuracy of 70% is observed in the peak hour (6-11) when the elevator's maximum traffic and a maximum number of passengers are observed, which increases the probability of the coincidence of determination of the required floor. The minimum value of 49% is during (19-6) when there are very few passengers. Hence, the model's accuracy depends on the traffic and the number of passengers expected by the lift, i.e., with increasing data, the accuracy of the model increases due to the increasing probability of corresponding to the initial and final destinations (floors) at the same time.

To this end, an event logging module has been developed to record calls and instructions from passengers using a link to the time of the event (Table 2). Given that it is unacceptable to alter the elevator control system without taking appropriate action, a microprocessor module has been developed, and its information transmission system is blocked. It only reads the information from the lift control busbar, assigns it accordingly, and stores it in the unit's memory. A precise recording of these controls will make it possible to follow the transport processes specific to the objects, which can be used to optimize the operation of the lifting devices. One module has been installed in a public building where passenger traffic is significant.

Interestingly, during the afternoon hours, the number of elevator calls on this floor decreases significantly, which can be used by the algorithm to optimize passenger wait times for transportation tasks. In buildings of this type, the staff is mainly responsible for issuing such a request since customers rarely need to move between floors of the building because related competencies are usually located on adjacent floors, and passengers choose to go up the stairs so as not to waste time waiting for the elevator. Similar observations were made in other public buildings, where the distribution of controls was strongly dependent on the type of functions performed by the various levels of the building. The observations made in residential buildings are much less varied, but their common feature is a significantly smaller number of transportation tasks on floors 1-3 during peak time (7: 00-8:00 and 16:00-17:00). Information obtained over a long time indicates that the intensity of elevator use depends on the season, time of day, and building functions. It can be seen that the schedule of queries moves very differently and depends a lot on the profile of the object, as well as the preferences of their residents and elevator users. Optimizing devices in an isolated computer system is a complex task that requires optimization algorithms based mainly on profile data.

Figure 3 Average number of passengers waiting on the floor



Results of implementing the algorithm developed to identify passengers. The experiment results showed that the most frequented floors in high-rise buildings are 1, 3, 9, and 12 floors. The results of the experiment yield average data from 50 skyscrapers in Moscow. For the results obtained, the statistical reliability of the results was $p<0.05$, the profiled passenger statistics have enabled harmonizing passenger wait times and passenger numbers on each floor. According to Figures 1 and 2, the developed technical solution prevents an unnecessary load on the equipment and the cost of passengers' time from waiting for an elevator.

The obtained data presented in Figure 3 also confirm the predictions of passenger behavior in the "elevator-passenger-flow" system. Moreover, according to the model's calculations, the number of passengers waiting on the elevator platform is 34% lower than the experiments' results. It was noted that passengers prefer to walk above a floor instead of waiting for the elevator. It is also independent of the floor level, which indicates a reduction in waiting for time and optimization of the elevator system. However, these data depend heavily on the schedule (weekday peak time) and season, as indicated above.

Figure 4 Relative average waiting time for standard elevators and elevators utilizing facial recognition technology

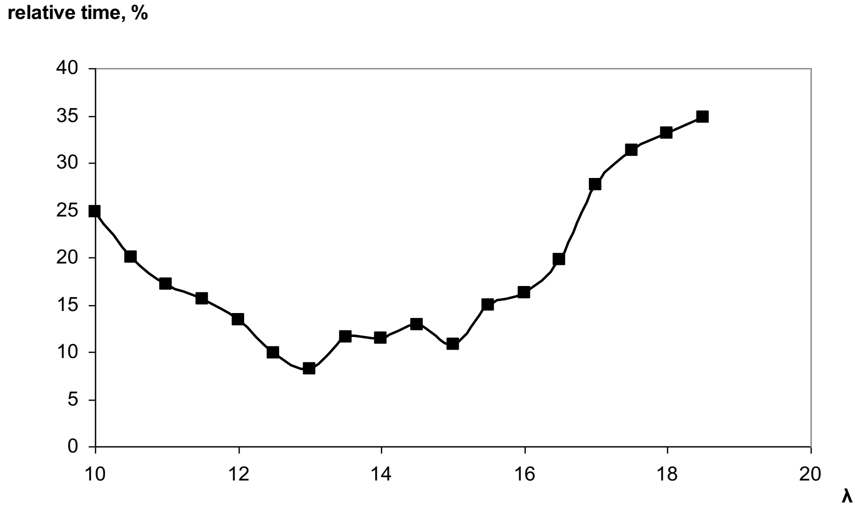


Figure 4 shows that, depending on the occupation of the elevator, the waiting time is not linearly dependent. It also depends on the number of floors and elevator cabins within the building. For example, the waiting time can be 25 to 40 minutes at lower occupancy, but the average elevator occupancy shows promising results in reducing the waiting time by more than twice.

4 Discussion

This paper proposes a way to resolve the problem of adjusting the operation of the lifts using a Markov process (Sabadash et al., 2020, Warr et al., 2015). Here, the problem of approaching through the maximum likelihood method of a discrete Markov chain in a finished state space was considered, which must be reversible over time. Several examples of modeling transport problems and calculating standard errors and confidence intervals for parameters can be found in the literature (Borucka, 2018; Bulat et al. 2016). The unique feature of the proposed methods is the availability of excellent initial values for optimizations, unlikely to regulate elevator robots using the Internet of Things. Maintaining the quality and continuity of transportation services requires a high level of vehicle and personnel preparation. The management and control of tasks carried out using mathematical models based on random Markov processes make it possible to evaluate and determine the optimization strategy. According to (Kozłowski et al., 2020), identifying random process data depends on determining the transition probability matrix between operating states. It is demonstrated that the values of the transition matrix are strongly dependent on the duration of the state.

The authors of Guang and Hui (2018) developed a thread pool with multiple queues with dynamic priority, effectively managing complex parallel algorithms. This process causes downtime, which is undesirable and requires qualified service personnel, adversely affecting operational costs. The drawbacks of such a system are also the high cost of equipment and maintenance. Elevator designs can be described using an algorithm based on Bayesian networks (Kolesov and Petrov, 2018). However, the Bayesian approach to the calculation of conditional probabilities is based on experimental findings. There is also a need to convert analog data into discrete values, requiring reasonably large computing power. The proposed model allows optimizing many elevator systems with one consistently scalable control algorithm. Due to the low efficiency of the monitoring microcontrollers, full implementation on them is almost impossible. As a result, it has to be implemented as a “web service” on an efficient central server with database connectivity. Such a solution would significantly increase the efficiency of lifting devices without interfering with their design and incur significant costs associated with the physical reconstruction of control systems (Ilina et al., 2014; Nutskova et al., 2019).

A web service with a powerful processing server retrieves the current command and call tables, optimizes them according to an algorithm based on fast access to historical data, and then sends an updated lift control command table (Kuchin et al., 2020). The availability of historical information on passenger flow and the ability to quickly implement the latest technical solutions covering a large group of devices logically working within one control system allows for better use of the elevator infrastructure. It increases the comfort of the elevator owner and users. The control system can collect all the manuals and settings for a particular elevator. Thanks to the authentication module, access to the button data in the lift cabin can be customized with an authorization card. The data processing authorization modules in the lifts do not need to be installed. There is only a need to provide a module to read the unique map ID. The three models are installed in the 632-meter-high building of China, the Shanghai Tower. The company received the Guinness World Records at a ceremony held on December 8, 2016, at the company's head office in Tokyo (Furgała et al., 2017; Kugiya et al., 2016). The elevator might be quite intelligent in the future SDGs. With Big Data and the Internet of Things (IoT) technology, no touch is required in the elevator cabin. The application may call the elevator and automatically send the passenger to the required floor. The mechanical engineering industry is currently exploring accurate rectangular target areas to determine the tendency of passengers on the site and avoid the false start of elevator calls (Ramalingam et al., 2016).

5 Conclusions

Based on the algorithms developed from daily passenger itineraries, the passenger occupancy on particular floors was forecasted. The passenger commuting models included in the central control room database will improve the accuracy of passenger forecasts based on the profile of a particular elevator. The algorithms developed will make it possible to implement a fast and reliable vertical transportation system. This study introduces a new approach to implementing the facial recognition apportionment of passenger elevators. A model is provided to calculate the likelihood of a passenger choosing one of the destination floors in real-time. The ability to apply profiled data will allow correlating the behavior of passengers and requests according to the statistics collected for profiled passengers. The efficiency of this elevator control algorithm is a global approach to saving resources and time for passenger service. The search results showed that the design solution would optimize the operation of the equipment by up to 34%. The proposed solution allows optimizing elevator systems with a constantly evolving control algorithm tailored to the customer's preferences and increasing SDGs.

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