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Modeling the aggregated power consumption of elevators – the New York city case study

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HIGHLIGHTS

\begin{itemize}
  \item Bottom-up model to evaluate the aggregate consumption of large elevator fleets.
  \item Model combines high-resolution passenger traffic and power demand simulations.
  \item High-resolution provides better understanding of the dynamic nature of elevators.
  \item Enables enhanced energy efficiency and retrofit studies.
  \item Can be used for detailed demand response potential analyses.
\end{itemize}

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ABSTRACT

This paper proposes a bottom-up framework for modeling the aggregated power consumption of a fleet of elevators. The paper has two aims: enhancing the research related to the power efficiency of elevators and providing modeling methods and analytical concepts for load modeling of elevators from the perspective of power systems and urban energy systems. As a case study, the paper simulates the total aggregated power consumption profile of elevators in New York City during a weekday and weekend day. Furthermore, the paper provides methods for expanding the analysis to other regions and cities which lack detailed background data of elevator installations. The results imply that elevators consume more than 1\% of the annual electrical energy in the city, while the hourly ratio has more variation, typically between 0.5\% and 3\% of the total power demand. Additionally, the quantity of elevators required to be modeled or measured from a random set to attain credible predictions of the total aggregated power consumption of the elevator population depends on the applied time resolution.

1. Introduction

Elevators (lifts) are highly intermittent electric power consumers. When transporting passengers, the instantaneous power consumption can be thousand times more than during standby. Moreover, each trip has a fairly unique power profile due to differences in loading, direction, and duration. This property prevents the straightforward analysis of instantaneous power demand of elevators and elevator groups. Consequently, the long-term energy consumption of these vertical transportation devices is blurred, and, for example, the effectiveness of energy efficiency improvements on individual installations, let alone the whole elevator stock, is uncertain.

The importance of modeling the elevator power demand and improving their energy efficiency has been amplified by their increasing role in the modern, urban society with the heightened demand for "green" products by the customers. Furthermore, the role of cities in the climate change and energy security has amplified [1], attracting significant research activity in the field of urban energy systems (UES).
According to [2], a UES model can be defined as “a formal system that represents the combined processes of acquiring and using energy to satisfy the energy service demands of a given urban area”. A typical goal of UES studies is to decrease greenhouse gas emissions [3], in which the first step is to model and simulate the behavior of the aggregated electrical load [4]. This information can be used, e.g., to enhance decision making on building retrofits and other energy efficiency improvements [5].

Load modeling, in general, has been widely acknowledged by the power system researchers, utilities, and system operators to secure efficient and reliable power system design and power generation scheduling. Resurfaced interest towards load modeling during the recent years has been caused by the introduction of new types of loads which offer enhanced control and higher efficiency [6]. For example, an increasing share of loads is driven by power electronics. Modern, high-performance elevators are nearly always equipped with a frequency-controlled drive, while, in the past, the elevators have been more or less directly connected. For instance, historically, hydraulic elevators were equipped with a single-speed electric motor operating the hydraulic pump and traction elevators were designed with rudimentary speed controllers, e.g., using relays [7].

As far as the authors are aware, the aggregated high-resolution power consumption of a large fleet of elevators, or even multiple elevator groups, has not been modeled or measured previously. Instead, a more common approach has been to calculate the daily and annual consumption estimates for individual elevators utilizing the specifications depicted in the VDI 4707-1 guideline [8] or the ISO 25745-2 standard [9]. However, calculating these estimates requires reference cycle measurements performed at the installation site, e.g., with a portable power meter. On the other hand, procuring more long-term measurement devices offers a convenient approach to create load profiles for individual elevator groups [10]. While the quantity of elevators under power monitoring is expected to increase in the future, their ratio is still minor and it is difficult to generalize the observations to large elevator populations with varying characteristics.

In addition to measurement-based approaches, various simulators can be utilized when the applied technology and other characteristics of the studied elevators are well known. These elevator energy simulation models have been, e.g., incorporated into existing elevator traffic simulators, such as in [11]. Alternatively, both the traffic and energy consumption models have been created [12], which also provides more freedom to test different scheduling algorithms, which has been done in [13]. Elevator manufacturers have also developed in-house software, which provide accurate results for specific elevator setups and control algorithms [14]. However, all these approaches have been employed to single elevator groups only, providing little guidance on the applicability of the simulators in analyzing large elevator populations with varying characteristics.

On a larger scale, an energy efficiency monitoring campaign of elevators and escalators evaluated in [15] estimates the total energy consumption of elevators in the EU-27 to be near 20 TWh annually, close to 1% of the total electricity demand in the region. Furthermore, the study assesses the potential savings obtainable by different levels of technological improvements. However, the intraday power demand profile is not analyzed, and the paper concludes that more research is needed in the area of estimating the demand and efficiency potentials. An attempt to estimate the hourly power profiles of elevators in the UK has been done in [16]. Nonetheless, these profiles rely on old survey and measurement data, presumably from the 1990s [17], and the method to derive the power demand profile is uncertain.

Motivated by the previous research and growing interest in elevator energy efficiency, and due to the lack of clear methods to model the instantaneous aggregate power demand of large elevator populations, this paper aims to provide approaches for modeling large amounts of elevators and their power consumption profiles during different day types. Employing the proposed approaches can be seen beneficial for multiple parties trying to understand the components related to load modeling and, e.g., the peak power demand in urban areas. Furthermore, understanding the energy usage characteristics of these vertical transports is the basis for their energy efficiency research.

For a given elevator or elevator group with known technical characteristics and monitored passenger flows, we have shown in [18] that credible intraday power profiles can be modeled with a relatively simple framework. In this paper, we expand the usage of this framework to model a large elevator population with varying characteristics. The focus is on the power system, or large-scale, perspective. As discussed in [18], for more detailed inspection of individual elevators or elevator groups, more accurate methods are available such as the aforementioned simulators and several patents, e.g., [19].

The paper is structured as follows. Section 2 briefly introduces the concept of random coincidence of loads and the smoothing effect on the aggregate demand curve. Section 3 presents the applied simulation approach the authors have depicted and tested in [18] to model the high-resolution power consumption of an elevator and elevator groups based on the simulated passenger traffic. Section 4 introduces the case study of New York City, which includes several types of buildings and traffic distributions for two day types: weekends and weekdays. In Section 5, the model is employed to simulate the aggregate power consumption of elevators in the case study. Section 6 discusses the applications where the model can be utilized and suggests potential improvements to the model. Section 7 concludes the main findings of the paper. Appendices A and B introduce the parameters and background data employed in the simulation of the case study.

2. Background of load aggregation

Modeling and predicting the aggregated consumption of intermittent loads is, at the same time, challenging but also alleviated in contrast to single loads with a random coincidence of power demand. The challenge arrives with the modeling of the interdependence between different consumer groups and due to the large variety of consumers with different time-domain characteristics and magnitudes of demand. Fortunately, when the quantity of consumers increases, the individual differences tend to be mitigated and a more probabilistic approach can be utilized to model and predict coincident power demand at an instant of time.

A typical application field for coincident demand analysis is the field of power transmission and distribution. For instance, the coincident peak demand experienced on the substation level is the key figure to consider when designing the substation which distributes power to the customers. Multiple approaches exist to model the total aggregated power consumption. These methods range from the time series analysis of the load data itself [20] to models employing the building characteristics in the region [21]. Short-term load modeling based on load data can be assisted with classical statistics or with machine learning methods [22]. The analysis can also be based on the fundamental phenomena behind the power demand, such as the activity and occupancy in the examined region. For instance, study [23] presents a modeling framework to obtain high-resolution stochastic series of domestic activity patterns and resulting electricity demand. The same study also discusses the smoothing effect the random coincidence has on the aggregate demand curve.

Regarding the analysis of coincident power demand, two important terms rise above others: the load factor and the diversity factor. The load factor is defined as the ratio of average power demand, \( P_{\text{average}} \), and maximum, or peak, demand, \( P_{\text{max}} \):

\[
\text{Load factor} = \frac{P_{\text{average}}}{P_{\text{max}}}.
\]

For the utility company, the optimal value would be 1.0, i.e., the power system utilization rate would be consistently at maximum [24]. A low load factor, on the other hand, leads to a power delivery system which
is oversized most of the time, meaning that the system efficiency is poor. On a large scale, this cumulates the pressure to increase distribution and transmission fees which, in the end, customers eventually have to pay for.

The diversity factor is a useful figure directly related to the coincidence of concurrent power demand by multiple loads. By definition, the diversity factor can be formulated as the ratio of maximum non-coincident demand (sum of individual maximum powers, \( P_{\text{max}_i} \)) and the maximum diversified (aggregate) system demand, \( P_{\text{max}_\text{sys}} \):

\[
\text{Diversity factor} = \frac{\sum P_{\text{max}_i}}{P_{\text{max}_\text{sys}}} \tag{2}
\]

The diversity factor is high when the individual loads are dispersed in time, i.e., their peaks coincide seldom, resulting in a low system-wide peak demand. On the other hand, the diversity factor can be near unity, for example, in a region where the consumers are highly alike, such as in a dedicated industrial park. An important characteristic of the diversity factor is that it saturates when the number of individual loads increases. This phenomenon is useful for designing, e.g., the low-voltage distribution grid, where, after a certain amount of households, the diversity factor can be considered as a constant, and the power system can be dimensioned according to the number of households with a known peak power (from main fuse sizes) divided by the diversity factor plus an additional safety margin.

From the elevator energy efficiency research point of view, the elevator-specific values of diversity and load factor provide valuable information on the large-scale usage patterns of these intermittent devices. Furthermore, the values enable the analysis of the impact of elevators on the electricity grid in dense, urban areas.

3. Simulation methods

To model the power consumption of a large population of elevators, this study employs common elevator power consumption equations which are based on basic mechanics. Furthermore, we adopt a group control scheme where the objective is to minimize the expected waiting time of passengers, resembling the estimated time of arrival (ETA) traffic control system presented in [25]. These approaches have been further analyzed in [18] by the authors. Prior to applying these methods, the background information on the characteristics of the elevator population and passenger traffic must be acquired, as explained next.

3.1. Elevator population and passenger traffic model

The elevator power consumption is a result of the electrical and mechanical properties of the elevator as well as of its usage. Fig. 1 introduces the applied elevator group and passenger traffic model applied in the case study to obtain the background information required for the simulation of the power profiles. Depending on the available data and other information about each specific case, the models could be altered. The main objective is to have an estimate of the amount and timing of the trips and the characteristics of the studied elevator population.

The main characteristics of the elevators are:

- number of served floors above the ground floor, \( n_{\text{floors}} \);
- rated load, \( m_{\text{rated}} \);
- building type, such as residential or office;
- number of trips per day (a trip comprises a movement of an elevator from one floor to another, loaded or empty, including acceleration, nominal speed, and deceleration periods as well as door operations), \( n_{\text{trips}} \);
- elevator group (bank) size, \( L \);
- and electrical and mechanical characteristics, such as nominal speed, car mass, applied hoisting technology, hoisting efficiency, and standby power.

The superscripts in each parameter box in Fig. 1 refer to the method of deriving the characteristics in question. These methods and related sources are listed in Table 1. The derivation of the parameter values and properties is introduced with the help of the case study in Section 4.

Due to the authors’ purpose to employ the models in evaluating the impact of different control actions on the aggregate power consumption of the elevator population, it is also beneficial to model the passenger traffic which generates the landing calls the elevator group needs to serve. To estimate the intensity of passenger traffic, we employ an adaptation of the usage categories proposed in the VDI 4707-1 guideline and the ISO 25745-2 standard. The usage category (UC) provides the typical number of trips an elevator executes during a day depending on the building type and height ranging from 50 (UC1) to 2500 (UC6) trips per day (see Appendix A, Table A.1). In our model, the total amount of trips inside an elevator group with \( L \) units is \( L \times n_{\text{trips,unit}} \). This value is then converted into the amount of passengers, \( n_{\text{passengers}} \), which approximately produces as many trips in the specified elevator group. The above process is discussed further in Appendix A.

The elevator usage depends on the passenger traffic distribution, which is specific to each installation. For modeling purposes, buildings can be segmented into building types which have unique passenger traffic distributions (see Appendix A, Fig. A.2). The distributions are employed with the following procedure which is repeated for each passenger (in total \( n_{\text{passengers}} \)).

1. The timing of a landing call is drawn from the stacked distribution of the three traffic components (incoming + interfloor + outgoing) of Fig. A.2.
2. Passenger’s movement objective (incoming, interfloor, or outgoing) is drawn for the corresponding period.
3. The origin and destination floors are determined for the different travel objectives with the rules provided in Table 2.
4. The probability of an origin or destination floor in the set of multiple possible floors is considered uniform with the exception of the effect of the stair factor for travel distances of less than six floors. The stair factor indicates the probability of a person taking the stairs instead of calling the elevator. The impact of this phenomenon on the \( n_{\text{trips}} \) is compensated with the correction factor discussed in Appendix A to preserve the overall usage level within the intended traffic intensity.

In the simulation, when the landing call is made, the group controller decides which elevator is assigned to handle the call as proposed in [18]. The objective behind the decision is to minimize the expected waiting time for the person placing the call. The elevators then execute the trips dictated by the group controller. The resulting elevator power consumption is then derived from these trips as explained in Section 3.2.

3.2. Power consumption model

In this study, the power consumption is simulated in one-second resolution. When depicting the simulation, it can be considered to consist of multiple layers. On the top level, the elevator is modeled to be either stationary or executing a trip between floors. When stationary, the ISO 25745-2 standard suggests three different stages of power consumption as depicted by Eq. (3).

\[
P_{\text{Stationary}}(t_s) = \begin{cases} 
P_{\text{idle}} & \text{for } t_s \leq 5 \text{ min} \\ 
P_{\text{standby, min}} & \text{for } 5 \text{ min} < t_s \leq 30 \text{ min} \\ 
P_{\text{standby, min}} & \text{for } t_s > 30 \text{ min} 
\end{cases}
\tag{3}
\]

where \( t_s \) is the elapsed time since the last stop. It should be noted, however, that a large quantity of the installed base of elevators is not equipped with these energy saving modes, i.e., the stationary power consumption equals to \( P_{\text{idle}} \). The power values as well the ratio of elevators simulated with the energy saving modes in the case study are
During a trip $i$, the instantaneous electric power demand of the elevator drive at time $t_i$ depends on the masses (the car mass, $m_{\text{car}}$, the mass of the load, $m_{\text{load}}$, and the rated load, $m_{\text{rated}}$) to be hoisted, the counterweight ratio, $K$, the sign and magnitude of speed, $v$, and acceleration, $a$, at time $t_i$ as well as the hoisting efficiency, $\eta$, which depicts the overall conversion efficiency between the electrical grid and mechanical movement of the elevator and counterweight:

$$P_{M_i}(t_i) = \begin{cases} \frac{1}{\eta} P_M(t_i) & \text{when } P_M(t_i) \geq 0 \\ P_M(t_i) & \text{when } P_M(t_i) < 0, \end{cases}$$

(4)

where

$$P_M(t_i) = \begin{cases} v(t_i) \cdot \left( (C_{M_i} + m_{\text{load}} + 2 \cdot m_{\text{car}} + K \cdot m_{\text{rated}}) \cdot a(t_i) + g \cdot (m_{\text{load}} - K \cdot m_{\text{rated}}) \right), \text{ for traction elevators,} \\ v(t_i) \cdot (m_{\text{car}} + m_{\text{load}}) g, \text{ for hydraulic elevators,} \end{cases}$$

(5)

provided in Appendix B.

During a trip $i$, the instantaneous electric power demand of the elevator drive at time $t_i$ depends on the masses (the car mass, $m_{\text{car}}$, the mass of the load, $m_{\text{load}}$, and the rated load, $m_{\text{rated}}$) to be hoisted, the counterweight ratio, $K$, the sign and magnitude of speed, $v$, and acceleration, $a$, at time $t_i$ as well as the hoisting efficiency, $\eta$, which depicts the overall conversion efficiency between the electrical grid and mechanical movement of the elevator and counterweight:

$$P_{M_i}(t_i) = \begin{cases} \frac{1}{\eta} P_M(t_i) & \text{when } P_M(t_i) \geq 0 \\ P_M(t_i) & \text{when } P_M(t_i) < 0, \end{cases}$$

(4)

where

$$P_M(t_i) = \begin{cases} v(t_i) \cdot \left( (C_{M_i} + m_{\text{load}} + 2 \cdot m_{\text{car}} + K \cdot m_{\text{rated}}) \cdot a(t_i) + g \cdot (m_{\text{load}} - K \cdot m_{\text{rated}}) \right), \text{ for traction elevators,} \\ v(t_i) \cdot (m_{\text{car}} + m_{\text{load}}) g, \text{ for hydraulic elevators,} \end{cases}$$

(5)

where $C_{M_i}$ is the inertia constant, further explained in Appendix B, and $g$ is the acceleration due to gravity. The sign of speed is selected positive when the elevator car travels upwards. If the elevator is non-regenerative, all the negative values of mechanical power demand, $P_{M_i}$, are set to zero. For example, all simulated hydraulic elevators are presumed non-regenerative in this paper. Moreover, for simplicity, the speed of the hydraulic elevator is presumed as a constant (nominal speed, $v_{\text{nom}}$) due to the low operational speeds.

The total power consumption during a trip is modeled as

$$P_{\text{trip}}(t_i) = P_{\text{elec}}(t_i) + P_{\text{control}} + P_{M_i}(t_i),$$

(6)

where $P_{\text{control}}$ depicts the increase of power demand by the control electronics during a trip (refer Appendix B for details). In addition to
the above equation, the power consumed by the door operations is inserted before and after the trip for a duration of two seconds.

In [18], we demonstrated the suitability of the above approach (power equations combined with the collective control where the elevator car is selected to minimize the passenger waiting time) to simulate the power consumption profile and daily total energy demand of an arbitrary elevator group with the process depicted in Fig. 2. In the case study, the differences in the group control methods between various elevator groups are presumed to even out on the aggregate level, justifying the use of the waiting-time based dispatcher.

4. Introducing the case study

New York City (NYC), particularly Manhattan, is a vivid example of a functioning high-rise city. Recently, high-rise construction has also been booming globally due to strong urbanization trend, especially in Asia. These tall cities can populate more vertical transports than many countries. Furthermore, these densely located elevators are high-speed and reach much higher heights than an average elevator, thus, demanding more from the electricity distribution system.

This section utilizes open data from NYC elevator and building characteristics to estimate the total power consumption profile of elevators in the city. According to [26], there were more than 75,000 registered vertical transportation devices in New York City in 2015. Nearly 70,000 of these were elevators, a figure we will also apply in the study. Interestingly, this exceeds the total number of elevators installed in Finland, for example, and equals to more than a quarter of elevators installed in the United Kingdom [30].

The top histogram in Fig. 3 shows the height distribution in terms of number of served floors above ground floor adapted from the [26] spreadsheet. Some values had to be excluded due to conformity errors appearing in the spreadsheet. Moreover, the few elevators exceeding a 5000 kg of rated load were excluded for simplicity due to their low quantity and probable usage in manufacturing. Nonetheless, the acquired profile was employed as the basis to distribute the modeled 70,000 elevator units. The large peak is due to the local building regulations favoring this building height. To calculate the hoisting related power and energy demand, the simulation model applied a fixed floor height of 3.6 meters.

Fig. 3 also reveals that the capacity (rated load) distribution of elevators was found to have several distinctive distributions depending on the number of served floors. With low-rise elevators, the rated load distribution was more spread due to physically smaller elevators installed in compact spaces and large hydraulic elevators for lifting heavy goods.

In the case study simulation, after the elevator group was drawn a height (in number of floors above the ground floor) according to the empirical top distribution in Fig. 3, the corresponding loading distribution of the specific floor range was applied to assign the rated load of the elevator group. The distributions were applied as shown in Fig. 3 – no further fitting was performed prior to simulations. The combination of the height and rated load also determines the probability of the elevator group to be equipped with a hydraulic hoisting technology instead of the traction-based solution (see Appendix B). Here, it should be noted that the term “cluster” in Fig. 3 is obtained by grouping similar elevators (number of floors and rated load) in a building together. Thus, they do not exactly depict the actual elevator groups. Instead, in the simulation, the elevators are divided so that no more than eight elevators are in one group, an approach suggested in [31] and applied, e.g., in [32]. The authors have estimated the group size dependence on the usage category (traffic intensity) by building type in Table 3, which is also applied in the simulation. For usage categories 2 – 3 and 4 – 6, the weighted probabilities for single-unit groups were 0.8 and 0.4, respectively. The probability for the larger group sizes were presumed uniform. This approach yielded around the same group size

![Simplified flowchart of the aggregate power consumption simulation. The simulations were performed in one-second granularity.](image-url)
distributions in the simulation as was suggested by the clusterization method mentioned above.

The usage of elevators is determined by the traffic profile of the building. For modeling purposes, the case study elevators are divided into buildings according to Fig. 4. The ratio of building types in each height category (in number of floors above the ground floor) is obtained by matching the addresses of the NYC elevator data set to the building type classification listed in the NYC Department of City Planning’s PLUTO dataset [27]. For the approximately 70,000 elevator units, 24,000 were found a match based on the reported addresses. The values have been calculated by assuming that the matched samples represent the distribution of the total population, i.e., there is no selection bias. Due to the low quantity of buildings exceeding the heights of more than 50 floors, the resulting overall distribution is relatively incoherent. Moreover, if no buildings were listed in a certain height category, the distribution was continued from the previous one.

To model the power consumption in these buildings, traffic profile distributions are needed both for weekdays and weekend. Appendix A presents the employed elevator traffic profiles. They are mostly based on the previous research work and observations in offices [10], retail environments [33], public transportation sector [34], hospitals [35] as well as in hotels and residential buildings [29]. Additional profiles are a combination of simplified versions of typical visitor profiles given by Google Popular times graphs and estimates by the authors.

The nominal speed of each elevator in the model is calculated by dividing the shaft height with $T$, where $T$ is a random number representing the time it takes to travel the whole shaft at nominal speed. The number is drawn from a distribution where there is a 80 percent chance for values between 20 and 30 s and 20 percent chance for values between 30 and 60 s. The smallest speed value is 0.1 meters per second. This is a rough estimate of the characteristics of the installed base of elevators but justified by a rational design guideline that traveling between terminal floors should take less than 30 s [32].

In the simulation, passengers not fitting into filled elevators will wait four seconds prior to making a new call. In addition, a one-second delay, $t_{load}$, is calculated for each passenger even though the passenger would be unable to board a maxed out elevator. The rest of the applied simulation parameters are presented in Appendix B.

With the help of the above background data and approaches presented in Section 3, it is possible to estimate the daily power demand profiles for the whole fleet of elevators. The results are analyzed in Section 5.

---

**Table 3**

Maximum number of elevators in a group for different building types depending on the usage category of the elevator group.

<table>
<thead>
<tr>
<th>ISO 25745-2 usage category</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Residential</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>Offices &amp; administrative/school</td>
<td>1</td>
<td>2</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>8</td>
</tr>
<tr>
<td>Hotels</td>
<td>1</td>
<td>2</td>
<td>4</td>
<td>6</td>
<td>6</td>
<td>6</td>
</tr>
<tr>
<td>Other</td>
<td>1</td>
<td>2</td>
<td>4</td>
<td>5</td>
<td>5</td>
<td>5</td>
</tr>
</tbody>
</table>

---

**Fig. 3.** Rated load distribution of unique elevator setups (clusters) and the number of clusters in terms of number of floors in NYC.
5. Case study results

This section portrays the attained momentary power profiles for a weekday and a weekend day for the case study. The elevators were generated in sets of around 100 units. Due to the probabilistic approach of modeling the elevator group sizes (see Table 3), there was variance in the number of units per set, and, thus, also in the total number of simulated elevators when the elevator population was redrawn.

The most important aim for this paper is to find the sample size which represents the total elevator population. Knowing the size of the representative sample helps to analyze the aggregated elevator power consumption more efficiently in future research. This is necessitated by the realization that running a large-scale simulation with multiple iteration rounds can take several days, as the simulation time is significant due to the intermittent passenger traffic and resulting elevator group control actions.

Fig. 5 shows the simulation results for a weekend day and a weekday. During the weekend, there is clearly less elevator usage due to office elevators being mostly idle. In addition, the morning peak is shifted by a few hours and the lunch time peak also slightly. Compared to the power volatility of single elevators, the aggregated power profile is much more consistent. However, it is relevant to note that the fluctuation within just a few seconds can still be up to seven megawatts during a weekday and six megawatts on a weekend day. Table 4 illustrates the main characteristics of the simulation and Fig. 6 the division of power demand between different usage categories and building types. Presuming a recurring weekly elevator usage through an entire year, the annual electrical energy consumption of elevators totals 671 GWh which constitutes more than 1.2% of the NYC total electricity usage [36], while the ratio of hourly powers ranges typically between 0.5% and 3%, depending on the season and the time of day [37].

To extrapolate to the total power and energy demand with enough precision and accuracy, we can analyze the behavior of the aggregate estimate based on different sample sizes. Fig. 7 presents the results of taking 20 samples of randomly selected elevator sets (containing around 100 units) with the number of elevator sets ranging from 1 to 250 during the weekday simulation. The same analysis for the weekend simulation revealed similar characteristics as can be deducted from Table 5. A major finding is that the total daily electricity consumption can be projected with good credibility with less than five percent of the...
total elevator population. Nearly the same holds for the minute-level power averages. Here, the number of elevators was considered sufficient when 95% of the random samples had less than 10% error. More precisely, the reported figures are determined when both of the 2.5th and 97.5th percentile lines have permanently crossed the boundary values. With the normalized root-mean-square error (NRMSE), we applied the relative value of 0.10 as the boundary value. Overall, the results suggest that the number of elevators necessitated to be analyzed in order to estimate the aggregate elevator power demand characteristics in a city such as New York depends on the applied resolution.

Referring back to the two important power system design factors, the load factor and the diversity factor (see Section 2), we can next examine these factors from the perspective of the elevators. From Table 4, we are able to deduct that the simulated load factor for a weekday was 0.58 and 0.62 for a weekend day when considering the one-second resolution. As can be seen in Fig. 7, when the averaging period increases, the load factor also increases because of the decrease in the observed peak power.

The value of the diversity factor can be obtained by comparing the sum of individual maximum loads to the system-level maximum power. Another suitable method is to compare the sum of rated powers to the maximum aggregate consumption. The methods likely provide different values for the diversity factor. For instance, during acceleration, an elevator can momentarily consume more than its rated nominal power.

Fig. 6 presents the results based on the latter approach for both a weekday and a weekend day. For the NYC elevators, the values saturate after approximately nine thousand units, and the median values after this point were simulated to be around 4.8 and 6.3 during the weekdays and weekends, respectively. From the power system designing point of view, the smallest value is the significant one, as the system components are dimensioned according to the maximum power flow. It should be acknowledged that although the diversity factor provides a good estimate of the actual peak power caused by the loads (here elevators), the values of one case study are not necessarily applicable to, e.g., another city or different city blocks. For example, the results for the Manhattan elevators are clearly different despite the fact that they comprise more than half of the elevators in NYC. Table 6 depicts the main differentiating characteristics of the whole city and the Manhattan area. The key difference is the height distribution (Manhattan has taller buildings than NYC on average) which impacts the building type distribution, usage category, and thus, the overall power demand profile. With more frequent trips, the diversity factor tends to decrease due to the higher probability of coincidental trips in the analyzed region. Moreover, as was illustrated earlier, the chosen averaging period also affects the calculations.

Table 4
An example of simulated aggregate elevator power and energy demand in NYC.

<table>
<thead>
<tr>
<th>Number of elevators</th>
<th>Peak power [MW] (1-s granularity)</th>
<th>Daily energy [MWh] (% energy consumed while stationary)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weekday</td>
<td>70,034</td>
<td>138.8</td>
</tr>
<tr>
<td>Weekend</td>
<td>106.0</td>
<td>1945 (27%)</td>
</tr>
</tbody>
</table>

Fig. 6. Composition of simulated aggregated power demand by usage category (UC) and building type in one-hour resolution during a weekday (top row) and weekend day (bottom row).
The novelty of the framework is the attained instantaneous power profile by day type for a variety of different building types. Especially, the aggregated profile of elevator power consumption enables enhanced analyses of peak power consumption in a building or larger region, which is an important aspect when sizing grid components. In addition, from the energy efficiency research point of view, the approach is a powerful tool when analyzing the large-scale impact of

Table 5
The number of elevators required to obtain credible predictions in the case study (thousands).

<table>
<thead>
<tr>
<th>Averaging period</th>
<th>Peak power</th>
<th>NRMSE</th>
<th>Daily energy</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1 s</td>
<td>5 min</td>
<td>1 h</td>
</tr>
<tr>
<td>Weekday</td>
<td>13</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Weekend</td>
<td>15</td>
<td>2</td>
<td>2</td>
</tr>
</tbody>
</table>

6. Discussion

The novelty of the framework is the attained instantaneous power profile by day type for a variety of different building types. Especially, the aggregated profile of elevator power consumption enables enhanced analyses of peak power consumption in a building or larger region, which is an important aspect when sizing grid components. In addition, from the energy efficiency research point of view, the approach is a powerful tool when analyzing the large-scale impact of
improving elevator energy performance, as indicated in Section 6.2. Furthermore, the authors are compiling a study about the potentials of employing different control methods of elevators to momentarily reduce the aggregated power consumption in order to participate in demand response markets.

In Sections 6.1–6.3, the authors would also like to list some considerations and suggestions for improving and applying the simulation in other cities and regions.

### 6.1. Potential improvements

First of all, it should be acknowledged that the power consumption
modeled in this paper was focused on the elevator units. Therefore, the elevator-related energy consumption in a building and the region can be significantly higher when the auxiliary power consumption of call panels, shaft lighting, and ventilation are considered. Moreover, high-power units without a regenerative drive require large cooling and ventilation units in the machine room, further increasing power demand during peak-traffic hours.

There are also some considerations to be taken into account when interpreting the results. For instance, garage floors (floors below the main entrance) were not considered separately but as a part of the total shaft height and passengers were also considered to enter and exit at the ground floor (at shaft height 0). This induces some inaccuracy to the model, but considering the overall model, which has multiple presumptions and simplifications, this is probably a relatively small imprecision.

To further improve the case study analysis, the addresses provided in the open-source elevator data could be overlaid on the city map, resembling the approach employed in [38]. The actual location of the elevators could be combined with the structure of the power distribution network to perform risk analyses and to locate possible issues, e.g., with component sizing during peak demand as well as to enhance the transition towards cleaner cities by better matching local generation, consumption, and demand side flexibility [39].

Lastly, the power demand of the control electronics during a trip, \( P_{control} \), and the applied traffic distribution profiles should be reassessed in future studies (see Appendices A and B for more details). The same applies for the formulas of inertia and inertia constant. For example, considering the mass of the ropes would increase the acceleration-

---

**Fig. 11.** Hourly power changes predicted by the random forest regressor when changing the mean parameter values of the simulated case study. For power saving modes, the adjustment was made by decreasing or increasing the number of elevator groups having the stationary power saving feature. For building type, regeneration, and hoisting type, the adjustment of ratios was done as listed in Table 7.
7. Conclusions

The presented model can be extended and modified to evaluate the power consumption of elevators in any city or region. The quality and quantity of the background data dictate the credibility of the obtained results.

For a general view, in the case where there are no statistics about the elevators, a floor area-based approach can be employed to assess the number of elevators in the region. According to the matching process of the elevator addresses with the building classification data, there is approximately one elevator per 4500 m$^2$ of gross floor area, which is in line with the rule of thumb value of 4600 m$^2$ for office buildings provided in [42]. Due to dissimilar peak traffic intensities [43], this ratio varies between different building types as listed in Table 8, which also depicts other parameter values which have been derived from the NYC elevator data set [26]. For a more precise estimate, the local guidelines and regulations related to the compulsiveness of elevator installations in certain type and height of buildings should be considered when evaluating the number of elevators.

6.3. Adapting the model to other regions

The proposed modeling approach includes multiple parameter values which were estimated from the available data. To understand the significance of the selected parameter values, a random forest regressor was employed to allow changing the parameter values more freely and obtaining the model output with an accelerated pace compared to the full-scale simulation of the NYC elevator population.

The random forest (RF) regressor was trained with a new data set containing equal ratios of different building types and heavily randomized input parameters (features, independent variables) of the elevator population and the resulting simulated hourly power profiles (dependent variables) on a weekday. Using the feature importance property of the trained RF fit, it is possible to evaluate the significance of each feature as a ratio of the entire fit. Fig. 9 illustrates the feature importance ratios when the RF was trained to predict the daily power profiles in one-hour granularity for a weekday. The more important the feature is, the more it decreases the variance in the predictions. It is good to note, however, that feature importance calculation methods suffer from bias [40], e.g., favoring features which have multiple categories [41] and thus giving lesser weight on features such as regeneration and hoisting type, which have only two feature categories. Nonetheless, considering that the most important features provided by the RF regressor are related to potential energy difference (height and rated load) as well as to power demand intensity and duration (nominal speed, hoisting efficiency, and idle power demand), the feature importance ratios provide information on the features which are significant contributors in elevator power demand.

A separate test set of elevators was used to verify the prediction accuracy of the trained RF regressor. The top plot in Fig. 10 illustrates the comparison of the obtained aggregate consumption calculated from the sum of predicted hourly powers of each elevator group. As the accuracy of the regressor was determined sufficient, it was also applied to predict the power profiles of the case study elevator groups. The bottom plot in 10 shows that the performance of the fit remained at the same accuracy level with the case study elevator groups even though the building type distribution was heavily populated by residential elevator groups.

Fig. 11 depicts the predicted effect of changing the mean feature values in the case study elevator population. As the height also has an impact on the nominal speed and number of trips, it has a significant role in the total power consumption. Other important parameters, as also suggested by the feature importance ratios, are hoisting efficiency, idle power consumption ($P_{idle}$), rated load, and counterweight ratio. It is good to note that, in the model, changing the rated load also affects multiple other parameters. Increase in the rated load increases car and counterweight masses, motor inertia, as well as the number of trips due to more simulated passengers. The impact of changing the traffic profile distribution is not illustrated as it is a direct derivative of the building type distribution. Moreover, the effect of adjusting the group sizes by deactivating the reactivating units in a multiunit elevator group to enable DR participation is analyzed in an upcoming publication and, thus, excluded from this paper.

6.2. Impact of input parameter values

The presented model can be extended and modified to evaluate the power consumption of elevators in any city or region. The quality and quantity of the background data dictate the credibility of the obtained results.

For a general view, in the case where there are no statistics about the elevators, a floor area-based approach can be employed to assess the number of elevators in the region. According to the matching process of the elevator addresses with the building classification data, there is approximately one elevator per 4500 m$^2$ of gross floor area, which is in line with the rule of thumb value of 4600 m$^2$ for office buildings provided in [42]. Due to dissimilar peak traffic intensities [43], this ratio varies between different building types as listed in Table 8, which also depicts other parameter values which have been derived from the NYC elevator data set [26]. For a more precise estimate, the local guidelines and regulations related to the compulsiveness of elevator installations in certain type and height of buildings should be considered when evaluating the number of elevators.
power consumption and applied the model to simulate the power demand of elevators in a case study of a large city. The case study employed data sets from New York City in order to evaluate the characteristics of approximately 70,000 elevator units. From the case study perspective, the simulations indicate that elevators consume more than 1% of the annual electrical energy consumption in the city, while the hourly power ratio varies roughly between 0.5% and 3%. In addition, the results suggest that residential and office elevators cover around 70% of the total elevator power consumption which is significantly higher on weekdays (∼120–140 MW during peak-traffic hours) than on weekends (∼90–110 MW during peak-traffic hours). However, the aggregate curve can have several megawatts of fluctuation within just a few seconds. Nevertheless, from the modeling point of view, the large quantity of elevators smooths the relative fluctuation of the aggregate demand in contrast to individual loads, thus, allowing design parameters such as a diversity factor to be utilized. This could potentially simplify the modeling in the future. Furthermore, understanding the effect of the applied time domain resolution will be a major contributor in enhancing the future research around the topic of elevator power consumption modeling, energy efficiency, and other topical areas, such as demand response.

The authors continue to work on compiling a framework for an elevator demand response platform, i.e., to find the costs (e.g., reduced traffic flow, inconvenience) and incentives (emission reductions, energy savings, monetary compensation) for each market side and participant that allow meaningful functionality of the demand response platform.

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This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. Declarations of interest: none.

**Appendix A**

This appendix contains the depiction of the traffic distribution profiles as well as the derivation of the number of trips, \( n_{\text{trips}} \), and the volume of passengers applied in the case study. The values are estimates and aim to represent the average characteristics of the existing elevator installations. The sensitivity of the model to the changes in the frequency of trips and building type ratio is analyzed in Section 6.2 of the paper.

The number of trips per day depends on the usage category of the elevator. The usage category is building type specific and relates also to the height of the building as depicted in the ISO 25745-2 standard, Annex A. For the simulation, the employed number of trips was randomized for each elevator group as depicted by Table A.1. Further, the number of trips during the weekend and weekday were made to differ from the randomly drawn number according to Table A.2 and Eq. (A.1).

\[
n_{\text{trips}} = \frac{1}{2} \left( 5 n_{\text{trips, weekday}} + 2 n_{\text{trips, weekend}} \right)
\]

(A.1)

The number of passengers was derived from the number of trips and average load suggested by the ISO 25745-2 standard. After simulating the number of trips in various traffic distribution profiles (see Fig. A.2), a compensation factor, \( f_k \), was introduced for each building type \( k \) to even the deviation difference from the desired number of trips and the simulated number of trips between the high- and low-traffic elevator groups in the final case study simulation. The resulting equations are

\[
n_{\text{passengers}, j} = \frac{n_{\text{trips}, j}}{f_k} \cdot \%Q \cdot \frac{m_{\text{rated}}}{m_{\text{passenger}}},
\]

(A.2)

\[
f_k = c_1(n_{\text{trips}, j})^{c_2},
\]

(A.3)

where \( n_{\text{trips}, j} \) is the number of trips to be simulated for a day type \( j \), \( \%Q \) is the ratio of average load with respect to the rated load, and \( m_{\text{passenger}} \) is the average mass of a passenger (here 75 kg). The coefficients \( c_1 \) and \( c_2 \) are provided in Table A.3. Fig. A.1 illustrates the obtained benefit of the approach: the uncertainty in the number of trips becomes more linear within the whole range of traffic intensity, when the building type-specific coefficients of the fitted curves, with similar form as in Eq. (A.3), are employed.

The employed passenger distributions for each modeled building type are displayed in Fig. A.2. For administrative/school buildings, the single-tenant office traffic profiles were utilized. In addition, 30% of all office elevator groups were modeled to belong to single-tenant offices and 70% to multi-tenant offices. Furthermore, 70% of garage and industry elevator groups were modeled according to the public transportation profile and 30% according to the airport profile. In addition, the entertainment category was subdivided into museums (30%) and theaters/arenas (70%). The passenger traffic distributions which were based mostly on estimates, i.e., airport, museum, and theaters/arenas, only comprised 2% of the total simulated elevator population.

<table>
<thead>
<tr>
<th>( n_{\text{floors}} ), (building type)</th>
<th>Usage category</th>
<th>( n_{\text{trips}} ), normally distributed</th>
</tr>
</thead>
<tbody>
<tr>
<td>( n_{\text{floors}} \leq 2 ) (50%)</td>
<td>1</td>
<td>( \mu = 50, \sigma = 12.5 )</td>
</tr>
<tr>
<td>2 (50%) ( \leq n_{\text{floors}} \leq 5 ) (or entertainment)</td>
<td>2</td>
<td>( \mu = 125, \sigma = 37.5 )</td>
</tr>
<tr>
<td>5 ( \leq n_{\text{floors}} \leq 10 ) (or airport (5% of public transport elevators) or hospital (( n_{\text{floors}} &lt; 4 )) or retail)</td>
<td>3</td>
<td>( \mu = 300, \sigma = 100 )</td>
</tr>
<tr>
<td>10 ( &lt; n_{\text{floors}} \leq 25 ) (or hospital (( n_{\text{floors}} \geq 4 ))</td>
<td>4</td>
<td>( \mu = 750, \sigma = 125 )</td>
</tr>
<tr>
<td>( n_{\text{floors}} &gt; 25 )</td>
<td>5</td>
<td>( \mu = 1500, \sigma = 250 )</td>
</tr>
<tr>
<td>( n_{\text{floors}} &gt; 25 ) (excluded in the case study, and trips limited to 2700)</td>
<td>6</td>
<td>( \mu = 2500, \sigma = 250 )</td>
</tr>
</tbody>
</table>

**Table A.1**

Determination of the number of trips per day per elevator. The usage category and standard deviation dependence on the building type and number of floors are estimated based on the ISO 25745-2 standard, Annex A [9].
Table A.2  
The ratio between the number of trips during weekdays and weekend.

<table>
<thead>
<tr>
<th></th>
<th>Residential</th>
<th>Offices</th>
<th>Hotel</th>
<th>Public transport</th>
<th>Retail</th>
<th>Hospital</th>
<th>Entertainment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weekday</td>
<td>0.95</td>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
<td>0.7</td>
<td>1.0</td>
<td>0.75</td>
</tr>
<tr>
<td>Weekend</td>
<td>1.0</td>
<td>0.05</td>
<td>1.0</td>
<td>0.75</td>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
</tr>
</tbody>
</table>

Check Table A.4 for the definition of the employed references expressed with the superscripts. 
Administrative/school elevators were presumed to have the same ratios as offices. 
The airport, garage, and industrial elevators were modeled with the public transport ratios.

Table A.3  
Coefficients for passenger volume generation.

<table>
<thead>
<tr>
<th></th>
<th>Residential</th>
<th>Offices</th>
<th>Hotel</th>
<th>Public transport</th>
<th>Retail</th>
<th>Hospital</th>
<th>Entertainment</th>
</tr>
</thead>
<tbody>
<tr>
<td>$c_1$</td>
<td>0.13</td>
<td>0.11</td>
<td>0.09</td>
<td>0.05</td>
<td>0.47</td>
<td>0.01</td>
<td>0.56</td>
</tr>
<tr>
<td>$c_2$</td>
<td>0.3</td>
<td>0.31</td>
<td>0.37</td>
<td>0.41</td>
<td>0</td>
<td>0.65</td>
<td>0</td>
</tr>
</tbody>
</table>

Administrative/school elevators were presumed to have the same coefficients as offices.  
The airport, garage, and industrial elevators employed the public transport coefficients.

Fig. A.1. Linearization effect of applying the compensation factors, $f_k$, in a sample of 1,000 elevator groups with varying characteristics.
This appendix presents the selected parameters for the case study and depicts the selection process of the model and simulation parameters. As in Appendix A, the values are estimates which aim to represent the average characteristics of the installed base of elevators. Nonetheless, the sensitivity of the model to the changes in these input parameters is extensively analyzed in Section 6.2 of the paper. Parameters explained in the main text are not necessarily reintroduced.

Table B.1 presents the parameters applied in the calculation of the elevator movement and consequent power requirement. The car mass, $m_{car}$, dependence on the rated load was derived from sampled elevators of a typical offering (see Fig. B.1), i.e., steel-framed cars. The impact of changing the applied frame structure is analyzed in Section 6.2 by changing the multiplier of $m_{rated}$ (default 0.456) in the car mass equation.

The inertia constant, $C_{JM}$, was employed to represent a coefficient of the mass of a typical traction motor setup to achieve a certain rated power. It aims to mimic the effect of inertia of the motor, wheels, and pulleys on the effective mass, and consequently, on the power demand during acceleration and deceleration. This simplified approach enables modeling a variety of elevators without presuming any physical dimensions for the motors. The effect of considering different motor technologies and their varying effective mass to be hoisted is analyzed in Section 6.2 by changing the multiplier (default 280 1/m$^2$) of the inertia constant equation in Table B.1.

The characteristics of elevator power consumption applied in the modeling are explained in Table B.2. The performance levels for running and idle/standby power demand are adopted from the ISO 25745-2 standard. The distribution of the specific running energy, $E_{spc}$, in the elevator population is an estimate by the authors. The given equation to derive the hoisting efficiency from the running performance level is a simple estimate because the running performance values also contain other types of energy consumption, such as the energy required by lighting and control electronics. The range of the hoisting efficiency is presumed to be between 30% and 90%. Each elevator in an elevator group is considered to have different traffic patterns.

Fig. A.2. Applied passenger traffic distributions for the case study. Vertical axis represents the 5-min probability of a passenger entering or exiting the building or traveling between the floors (interfloor). See Table A.4 for the explanation of the superscripts.

Table A.4

<table>
<thead>
<tr>
<th>Sources/methods</th>
<th>1)</th>
<th>2)</th>
<th>3)</th>
<th>4)</th>
<th>5)</th>
<th>6)</th>
<th>7)</th>
<th>8)</th>
<th>9)</th>
<th>10)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Publication</td>
<td>[29]</td>
<td>[10] and related measurements</td>
<td>[34] and related measurements</td>
<td>[44] and related measurements</td>
<td>Weighted visitor and bed elevator profile [35]</td>
<td>Visual inspection of Google popular times of sample buildings</td>
<td>Estimated distribution profile shape by the authors</td>
<td>Estimated division of traffic types (traffic mix) by the authors</td>
<td>CIBSE Guide D 2005 [45]</td>
<td>Estimated by the authors</td>
</tr>
</tbody>
</table>

Appendix B

This appendix presents the selected parameters for the case study and depicts the selection process of the model and simulation parameters. As in Appendix A, the values are estimates which aim to represent the average characteristics of the installed base of elevators. Nonetheless, the sensitivity of the model to the changes in these input parameters is extensively analyzed in Section 6.2 of the paper. Parameters explained in the main text are not necessarily reintroduced.

Table B.1 presents the parameters applied in the calculation of the elevator movement and consequent power requirement. The car mass, $m_{car}$, dependence on the rated load was derived from sampled elevators of a typical offering (see Fig. B.1), i.e., steel-framed cars. The impact of changing the applied frame structure is analyzed in Section 6.2 by changing the multiplier of $m_{rated}$ (default 0.456) in the car mass equation.

The inertia constant, $C_{JM}$, was employed to represent a coefficient of the mass of a typical traction motor setup to achieve a certain rated power. It aims to mimic the effect of inertia of the motor, wheels, and pulleys on the effective mass, and consequently, on the power demand during acceleration and deceleration. This simplified approach enables modeling a variety of elevators without presuming any physical dimensions for the motors. The effect of considering different motor technologies and their varying effective mass to be hoisted is analyzed in Section 6.2 by changing the multiplier (default 280 1/m$^2$) of the inertia constant equation in Table B.1.

The characteristics of elevator power consumption applied in the modeling are explained in Table B.2. The performance levels for running and idle/standby power demand are adopted from the ISO 25745-2 standard. The distribution of the specific running energy, $E_{spc}$, in the elevator population is an estimate by the authors. The given equation to derive the hoisting efficiency from the running performance level is a simple estimate because the running performance values also contain other types of energy consumption, such as the energy required by lighting and control electronics. The range of the hoisting efficiency is presumed to be between 30% and 90%. Each elevator in an elevator group is considered to have different traffic patterns.

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### Table B.1
Parameters for kinetics.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Car mass [kg], ( m_{\text{car}} )</td>
<td>( 0.456 \cdot m_{\text{rated}} + 550 ) kg, see Fig. B.1</td>
</tr>
<tr>
<td>Probability for being hydraulic ( \ast )</td>
<td>80%, when ( n_{\text{floors}} &lt; 8 ) and ( m_{\text{rated}} \gtrsim 2000 ) kg, 50%, when ( n_{\text{floors}} &lt; 8 ) and ( m_{\text{rated}} \lesssim 2000 ) kg</td>
</tr>
</tbody>
</table>

#### Traction elevator

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Acceleration and deceleration</td>
<td>1.0 m/s²</td>
</tr>
<tr>
<td>Counterweight ratio, ( K )</td>
<td>44% of the time: 0.5</td>
</tr>
<tr>
<td>Rated motor power [kW], ( P_{\text{rated}} )</td>
<td>( m_{\text{rated}} \cdot \gamma_{\text{vem}} \cdot (1 - K)/\eta / 1000 )</td>
</tr>
<tr>
<td>Motor inertia [kgm²], ( J_M )</td>
<td>( 0.06 \cdot P_{\text{rated}} / 0.3 \cdot \text{kgm}^{2} )</td>
</tr>
<tr>
<td>Inertia constant [kg], ( C_{J_M} )</td>
<td>280 ( \text{kgm}^{2} \cdot \text{m} / \text{s}^{3} )</td>
</tr>
<tr>
<td>Roping ratio, (( \Omega ))</td>
<td>1:1</td>
</tr>
</tbody>
</table>

#### Hydraulic elevator

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rated motor power [kW], ( P_{\text{rated}} )</td>
<td>( (m_{\text{rated}} + m_{\text{car}}) \cdot \gamma_{\text{vem}} / \eta / 1000 )</td>
</tr>
</tbody>
</table>

\( \ast \) This results in around the same ratio (22%) of hydraulic elevators in the elevator population as in Europe (23%) [30].

---

![Fig. B.1. Typical car masses for different rated loads and the fit applied in the simulation.](image)

### Table B.2
System efficiency and power consumption characteristics.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Specific running energy, ( E_{\text{nr}} ) [mWh/kgm]</td>
<td>Normally distributed ( \mu = 2.2, \sigma = 0.7 )</td>
</tr>
<tr>
<td>Running performance level, ( p_{\text{FR}} )</td>
<td>1. when ( E_{\text{nr}} \lesssim 0.72 )</td>
</tr>
<tr>
<td></td>
<td>2. when ( 0.72 &lt; E_{\text{nr}} \lesssim 1.08 )</td>
</tr>
<tr>
<td></td>
<td>3. when ( 1.08 &lt; E_{\text{nr}} \lesssim 1.62 )</td>
</tr>
<tr>
<td></td>
<td>4. when ( 1.62 &lt; E_{\text{nr}} \lesssim 2.43 )</td>
</tr>
<tr>
<td></td>
<td>5. when ( 2.43 &lt; E_{\text{nr}} \lesssim 3.65 )</td>
</tr>
<tr>
<td></td>
<td>6. when ( 3.65 &lt; E_{\text{nr}} \lesssim 5.47 )</td>
</tr>
<tr>
<td></td>
<td>7. when ( E_{\text{nr}} \gtrsim 5.47 )</td>
</tr>
<tr>
<td>Hoisting efficiency, ( \eta )</td>
<td>0.9 + (0.3 - 0.9) ( \cdot (0.72 - E_{\text{nr}}) / 0.72 ) ( \cdot \max(\eta_{\text{nr}}, 0.72) )</td>
</tr>
<tr>
<td>Idle/standy performance level, ( p_{\text{FR}} )</td>
<td>40% of the time: ( p_{\text{FR}} = 1 )</td>
</tr>
<tr>
<td></td>
<td>40% of the time: ( p_{\text{FR}} &lt; 1 )</td>
</tr>
<tr>
<td></td>
<td>20% of the time: ( p_{\text{FR}} = 7 ) ( \cdot \min(\eta_{\text{nr}}, 0.72) )</td>
</tr>
<tr>
<td>Idle power consumption [W], ( P_{\text{idle}} )</td>
<td>Power, uniform distr. 50 ( \cdots 100 )</td>
</tr>
<tr>
<td>Probability for power saving modes (stationary)</td>
<td>10%</td>
</tr>
<tr>
<td>Five-minute standby power [W], ( P_{\text{standby,5min}} )</td>
<td>0.8 ( \cdot P_{\text{idle}} )</td>
</tr>
<tr>
<td>Thirty-minute standby power [W], ( P_{\text{standby,30min}} )</td>
<td>0.5 ( \cdot P_{\text{idle}} )</td>
</tr>
<tr>
<td>( P_{\text{com}} ) [W]</td>
<td>400 [46]</td>
</tr>
<tr>
<td>( P_{\text{car}} ) [W]</td>
<td>Uniform distribution, 200 – 1000</td>
</tr>
<tr>
<td>Regeneration ratio</td>
<td>10% chance of a regenerative elevator when usage category &gt;3.</td>
</tr>
</tbody>
</table>
the same characteristics. The value of power consumption for control electronics during a trip, $P_{\text{control}}$, is selected to correspond to the value of 400 W suggested in the ISO 25745-3 standard [46], which provides energy calculation and classification methods for escalators and moving walks. Power demand of the doors, $P_{\text{doors}}$, is modeled to occupy two seconds before and after each trip. The regeneration ratio is set at a relatively low level – around ten percent of elevator groups which are in the top 50% of all simulated elevator groups in terms of number of trips are simulated as regenerative. In the case study, the top 50% corresponds to elevator groups which belong to a usage category of 4 or higher (see Table A.1 and ISO 25745-2, Annex A).

Appendix C. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.apenergy.2019.113356.