

Artificial Intelligence in Lift Systems

Matthew Appleby

Peters Research Ltd, UK

Keywords: Artificial Intelligence, Elevator systems, Dispatching, Preventive maintenance, Expert design, System modelling

Abstract. Artificial Intelligence (AI) is playing an increasingly significant role in the lift industry, offering the potential to enhance efficiency, reliability, and passenger experience. This paper examines the application of AI across five core areas: dispatching, preventive maintenance, traffic pattern recognition, expert design, and system modelling.

In addition to reviewing existing research and practical implementations, it explores potential future developments, considering how AI could reshape the operational landscape of vertical transportation.

The ethical implications of AI adoption are also discussed, with particular attention to privacy concerns, workforce impacts, and the challenge of balancing parameter optimisation. This paper highlights the transformative potential of AI within the lift industry while emphasising the importance of ethical and sustainable implementation.

1 INTRODUCTION

1.1 Background

For thousands of years, humans have been automating work. Automation is the use of technology to perform tasks with minimal human intervention. Historically, the work being automated was routine manual labour that did not require intelligence. Artificial intelligence (AI) refers to machines' ability to perform tasks typically associated with human intelligence.

AI has impacted many industries and will continue to do so in the next few decades, changing how people work. One of the industries that has been and will continue to be impacted is the vertical transportation industry. There are a few areas in which researchers have attempted to apply AI in this industry with varying success.

1.2 Forms of AI

1.2.1 Knowledge-based system

A KBS is a computer system that uses logical reasoning and knowledge to solve problems. The system uses a repository of facts, rules and procedures, and an inference engine that applies the rules to make decisions.

1.2.2 Fuzzy logic

FL is a computational approach to dealing with uncertainty. Unlike the well-defined knowledge of a KBS, FL deals with uncertain or changing knowledge. FL works by converting crisp input values into fuzzy values between 0 and 1. Rules are then applied to the fuzzy inputs and a fuzzy output is generated. The fuzzy output is converted back to a crisp value which will determine an action.

1.2.3 Artificial neural networks

ANNs work by passing inputs through a set of artificial synapses and neurons with associated weighting to find an output. Based on the output, the weighting is changed to improve its accuracy. Unlike FL, ANNs use machine learning based on training data to improve.

1.2.4 Genetic algorithms

GAs also use machine learning, but instead of simulating a brain, they simulate biological evolution. An initial population of random solutions all try to solve the same problem; those that do better are used to create the next generation of solutions. Each generation makes slight random adjustments to the most successful solutions from the previous generation. Over multiple generations, better solutions are created.

2 LITERATURE REVIEW

This literature review summarises the existing research on using Artificial intelligence in lift systems.

2.1 Dispatching

Dispatching is the process of allocating lifts to calls. While simple rules can be used for dispatching, AI can potentially improve performance. [1]

Researchers first started looking at applying AI to lift dispatching in the early 90s when Deven and Chengdong [2] proposed using Fuzzy Logic (FL) to optimise multiple parameters when assigning cars to calls. Two years later [3] implemented and verified this approach in simulation.

A few years after that, researchers began investigating Artificial Neural Networks (ANN) for lift dispatching [4]. As ANN technology advanced, so too did its use in lift-dispatching [5] [6] [7].

Researchers have also experimented with using Genetic Algorithms (GA) to dispatch in more complicated lift systems, such as systems with double-deck lifts [8] [9] [10].

Basagoiti, et al. [11] proposed using data about past traffic flow to predict future traffic and thus improve the dispatcher. This study was based on simulated passengers and was not implemented in a real system.

Peters [1] published a paper discussing existing AI research on dispatching and evaluated which aspects of AI were most useful for a dispatcher. Peters implemented AI logic into a dispatcher which worked in both simulation and in real-world lift systems. This AI logic was carried forward to ‘The Global Dispatcher’ [12], which is a single dispatching algorithm capable of dispatching complex lift systems such as double-deck and two cars per shaft.

2.2 Preventive maintenance

As with all physical machinery, lifts must be regularly maintained to prevent failure during peak usage. All potential break points must be tested as just one break point could cause the system to fail. If monitoring systems could predict failures before they occur and accurately identify damaged components, maintenance could become less frequent and more targeted.

Researchers started discussing AI in preventive maintenance in the early 1990s [13] but little progress was made due to the complexity of the hardware needed to monitor a moving lift car and feed data back to a central computer. As other technologies such as IOT, big data, cloud computing and sensor fusion began to emerge, preventative maintenance became a practical possibility from the 2010s onwards. [14] [15] [16].

Kaczmarczyk et al. [17] developed an AI model that used vibration data to detect and classify damage in lift doors. The model used ANN with supervised learning and consistently demonstrated a 97.9% accuracy in damage classification. The following year, the same authors published a paper specifically on roller-bearing damage [18]. While the 2022 model classified existing damage, the 2023 model could also predict damage during the early stages, facilitating preventive maintenance. Data-driven preventive maintenance using this technology could transform the way that service personnel do their job, as Smith [19] predicts.

Most research on preventive maintenance has used vibration data but some researchers have explored the use of other sensors to monitor component health. Seyyedi et al. [20] used high-speed cameras to gather data about lift rope fatigue. The researchers trained an AI image processing system to classify different types of broken wires. Four cameras, each covering a 90-degree rope segment, continuously took pictures and sent them to a computer with an AI image processing module.

Sensor fusion is the process of reducing uncertainty by combining data from multiple sources [21]. Smans [22] suggested fusing data from optical sensors, accelerometers and barometric pressure sensors to detect failures in lift doors. By combining data from these diverse sensors, Smans demonstrated that the accuracy and reliability of door failure detection improved significantly compared to using single-sensor methods.

2.3 Traffic pattern recognition

A car call does not always correspond to one passenger, as groups of people going to the same floor might only register one call. Accurately measuring passenger traffic can improve dispatching and preventive maintenance logic.

Siikonen & Kaakinen [23] discuss using carload, calls and time of day to estimate the passenger flow. Siikonen wrote a further paper explaining how the system works using FL and how it can improve dispatching [24]. So, et al. [25] proposed a similar idea using ANN which they implemented in a Hong Kong building. However, its accuracy was less than 35% due to the training not being comprehensive enough.

Guidotti [26] described the use of AI to process data from infra-red beams in the lift doors which counts passengers in and out of a lift. This gathers information about passengers by processing data from a light curtain, a technology already essential for safety. The accuracy of the information can be improved when processed in conjunction with accelerometer data from the lift. This data-gathering method is less intrusive than a camera as the scanned image doesn't show people in sufficient detail to identify them.

The I-S-P (Inverse Stops to Passengers) method [27] predicts the number of passengers based on the number of stops and can be used to estimate the building's traffic flow. The I-S-P method can use traditional methods such as a rearranged form of the uppeak calculation or the Monte

Carlo Simulation as described by Al-Sharif et al. [28]. The I-S-P method can also use AI by training a model with simulation data. Al-Sharif et al. [29] demonstrated that a regression model can be trained to do an I-S-P analysis. However, further research is needed to demonstrate that the AI I-S-P method offers improvements when compared to the traditional I-S-P method.

2.4 Expert design

An essential step in building design is determining what sort of lift system is needed to lift a building with a given population and number of floors. This historically required an expert in traffic analysis.

An expert system is a computer system designed to model the knowledge of human experts. An expert design system is an expert system which designs lift systems. ISO 8100 – 32 [30] and CIBSE Guide D [31] each provide a set of rules, based on practices from industry experts, which can be used to design a lift system.

Prowse, et al. [32] describe an approach to lift system design using KBS. They also suggested a solution using an ANN.

Peters & Dean [33] used CIBSE guidance in a KBS to create an expert system which designs buildings to the CIBSE specification. Peters & Dean suggested in this paper's conclusion that applying fuzzy rules is an alternative to investigate in the future.

2.5 System modelling

Some attempts to use AI in the lift industry have been more successful than others. Sometimes, this is because the technology doesn't yet exist to make it work, and sometimes, it is because the problem doesn't lend itself to an AI solution.

Tolosana, et al. [34] applied ANN to lift system modelling. A model was trained on simulation data and could predict the round-trip time. The study demonstrated that under narrow constraints, there was a correlation between the simulated results and the ANN results. Although there was a correlation, there was too much variance between the ANN model and the simulation to rely on the ANN model for building design.

3 FUTURE DEVELOPMENT

The previous section of the paper investigated existing concrete research on the use of AI in lift systems. Instead, this section speculates on the trajectory of the lift industry based on current trends.

3.1 Dispatching

Dispatching systems are likely to use more sophisticated machine learning algorithms to adapt dynamically to complex passenger behaviours and building-specific traffic patterns.

Historical traffic data coupled with real-time analysis from multiple IoT sensors on the lift car will enable dispatchers to make better decisions. Predictive dispatching that anticipates demand spikes or reduces bottlenecks as well as passenger-specific dispatching which accounts for accessibility needs or priority handling can improve passenger satisfaction.

AI systems may be used to optimise the dispatcher for energy efficiency, balancing operational costs with environmental sustainability. Providing the dispatcher with real-time data about the energy consumption of the lift could help to improve dispatcher decisions over time.

3.2 Preventive maintenance

As sensors become more reliable and AI tools grow more adept at identifying faults, preventive maintenance is expected to become increasingly accurate, precise and timely. Technologies such as advanced vibration analysis, high-speed image recognition, and sensor fusion will play a key role in detecting faults early and classifying damage with greater precision. When combined with real-time operational data, these insights will allow future systems to anticipate failures and understand their potential ripple effects, enabling proactive and targeted interventions. A scalable IoT ecosystem will support this by continuously gathering and processing sensor data, ensuring that issues are identified and addressed in real time. AI systems could also recommend cost-effective maintenance schedules based on component wear rates and usage patterns, reducing downtime and resource wastage.

3.3 Traffic pattern recognition

Intelligent dispatching and preventive maintenance sensors will collect vast amounts of data. AI may be able to process this data, achieving near-perfect accuracy in counting passengers and predicting flow. Future systems might use historical traffic data and contextual data, such as weather, public holidays or events, to predict passenger demand more accurately. These predictions can feed into dispatching algorithms, ensuring lifts operate at peak efficiency while minimising passenger waiting times and energy consumption.

3.4 Expert design

Expert design systems currently use a KBS and a set of uppeak calculations to design a lift system based on a basic building design. Some authors have suggested using more advanced AI models such as FL or ANN. However, these advanced models are less transparent and less accountable for the design decisions they make.

So long as expert design systems rely on uppeak calculations, it will not be possible to use expert design for advanced buildings, such as those with a mixed traffic flow. The inclusion of general analysis calculations or simulations in an expert design system would have a greater impact on the utility of such a system.

3.5 System modelling

Some elements of system modelling can be improved with AI. The improvements to traffic pattern recognition can be used to create more realistic simulated passengers in traffic analysis. As dispatchers improve in real-world lift systems due to AI enhancements, the dispatchers in simulations will also need to improve to accurately model real-world systems.

Other elements, such as ideal lift kinematics, are best performed by computational logic and will remain in the domain of predictable maths equations.

4 IMPLICATIONS, RISKS AND ETHICS OF AI IN LIFT SYSTEMS

4.1 Dispatching

4.1.1 Impact on operators

When lifts were first invented, they were operated by trained employees. Passengers would tell their operator which floor they wanted, and the operator would take them there. By the 1970s, automated lifts had replaced the role of lift operators, and the job became redundant.

Improvements to lift dispatching algorithms can now happen without losing any jobs. The lift operation jobs no longer exist so improvements can be made without the ethical consideration of job redundancy.

4.1.2 Optimisation

4.1.2.1 Background

A dispatcher needs to balance various parameters when dispatching lifts to floors and allocating passengers to lift cars. Each decision a dispatcher makes will have an impact on the following parameters.

4.1.2.2 Journey time

The quicker an employee gets to their desk, the more work gets done and the more profits the organisation can make. Therefore, the priority should be to minimise the time between an employee pressing the call button and the lift arriving at the employee's destination.

4.1.2.3 Waiting time

Passengers are more satisfied when they are in the lift and moving somewhere than when they are waiting for the lift, according to Bird et al. [35]. This means that when a dispatcher sacrifices journey time to reduce waiting times, passengers are happier.

4.1.2.4 Travel time

All research into the correlation between travel time and passenger satisfaction was conducted before the Covid-19 pandemic. As a result, we do not yet know if the pandemic has changed societal expectations and passenger preferences with concerns about enclosed spaces leading to a shift in priority from travel time to waiting time. In such a scenario, passengers may have preferred lower lift occupancy, even if it resulted in longer waiting times.

4.1.2.5 Accessibility

Door dwell times can be reduced to reduce waiting and travel times. Lower dwell times mean the lift spends less time stopping at each floor. On the other hand, reduced dwell time makes the lift less accessible for those with impaired mobility who need longer to get to the lift.

4.1.2.6 Energy

As the impact of the impending environmental crisis becomes more visible, organisations will have to be seen as making a difference. One way to reduce a building's energy consumption is to use a dispatcher that minimises the energy consumption of the lift system.

4.1.2.7 Money

Some building providers have started offering premium prioritisation where clients who pay more get a better lift service. Under this system, when a premium passenger calls the lift, the

dispatcher will prioritise getting that passenger to their destination over serving other passengers in the system. Although this would be good for the premium clients, this would increase journey times for the other passengers and would increase the average journey time for the building.

4.1.2.8 Decisions

A dispatcher could minimise waiting times by always sending the nearest car to collect each passenger, but this decision is likely to increase journey time. Conversely, a dispatcher could assign a car per passenger which would reduce journey time, but this decision would increase waiting time. Making the decision to reduce door dwell time might reduce both journey and waiting times, but it is likely to make the system less accessible to some passengers.

The AI logic used in the dispatcher can help balance each decision to meet target outcomes, but AI cannot assess which parameters are more important. Prioritising parameters is an ethical dilemma that should be agreed upon by humans for the AI to obey, not the other way around.

4.2 Preventive maintenance

AI can predict and categorise failures in lift systems, enabling intelligent preventive maintenance. Preventive maintenance can be done during off-peak periods, meaning more lifts will be in service during peak usage. Over time, this will reduce the need for system redundancy, so fewer lifts will be needed in new buildings, which could positively impact cost and carbon emissions.

4.2.1 Monitoring systems

4.2.1.1 Image-based passenger recognition

AI image recognition has grown massively in the past decade, but ethical concerns are also growing.

AI can now accurately count the number of humans in an image, differentiating between humans, bags, dogs, pushchairs and anything else that might end up in a lift. AI has even reached the point of object permanence, the understanding that if a person goes out of view and comes back into view, they are still the same person. Camera-based analysis can provide more accurate data about traffic flow than can be provided by a weight-based analysis.

On the other hand, having a camera in the lift car will leave some passengers concerned about their personal privacy, especially if the footage is analysed in the cloud by a third party. One of the best ways to ensure object permanence is to use facial recognition. Companies that already track users' actions online for targeted advertisements could use this data to improve their digital user profiles. In the hands of an authoritarian government, facial recognition data could be used for invasive surveillance and control of citizens.

One solution is to use 'fog computing' by analysing the footage close to the source and only uploading the traffic data with no footage or details about specific passengers. This justification might be enough for some, but others would still be concerned by any form of camera in their lift car.

Another solution is to use less detailed data such as the readings from a light curtain over time. This data can be used to generate a 2D map of a person which can be used for passenger

counting but it is harder to use this kind of data to count people when their 2D map is irregular. This can happen for a variety of reasons, such as if a person is in a wheelchair or carrying a pushchair or shopping trolley.

4.2.1.2 Accelerometer-based failure recognition

Using a supervised ANN, a model can be trained to recognise damaged components based on the frequency and intensity of vibration data. This model can detect damage, locate the damage, classify the type of damage, assess the extent of the damage, and predict the residual life before the damage becomes critical. Most lift installation faults occur in the doors, so identifying door damage is the priority. Eventually, an array of accelerometers could monitor the entire system.

If this is monitored accurately, the data can be used to aid preventive maintenance. When preventive maintenance is assisted by AI data analysis, this is known as data-driven preventive maintenance and could have a massive impact on the whole industry.

The data gathered from monitoring lift health could be used to improve lift simulation. If a simulation could provide an approximate maintenance frequency with and without data-driven preventive maintenance, it would help building providers calculate whether the additional sensor costs are worth the investment.

4.2.2 Impact on technicians

Preventive maintenance is when a lift is inspected or serviced even if it is not out of service. This means lifts will spend less time out of service during peak usage times as servicing can be scheduled for off-peak times. Currently, technicians are given a list of lifts to be inspected (looked at) or serviced (actively changed) and will do these maintenance visits at a regular frequency. Technicians must have the skills, parts and tools to assess, adjust or replace anything that is wrong.

With data-driven preventive maintenance, fewer manual inspections must be carried out, as the lift is constantly being inspected by the automatic sensors. AI monitors and analyses the wear on each component in real-time, so replacements only occur when needed instead of regularly replacing components. Technicians will be given a list of tasks to perform on each lift, along with which parts and tools will be needed for the job.

4.2.2.1 Advantages

As a result of data-driven preventive maintenance, lifts will require less manual inspection and will spend less time out of service. Technicians will have more time to focus on fixing the problems as they will spend less time doing unnecessary regular inspections and servicing. This also means that fewer technicians are needed to maintain the same number of lifts thus reducing maintenance costs.

4.2.2.2 Disadvantages

The financial savings from reducing the frequency of routine maintenance must be weighed against the upfront and ongoing costs of installing and managing the necessary sensors and processors. These sensors need to be installed on the lift, a process that may require specialised technical expertise. Furthermore, the data collected must be analysed in real time and stored securely in a format that is both accessible and reliable, typically using internet-based systems.

This shift introduces new demands in terms of infrastructure and cybersecurity, which can increase the overall complexity and cost of the maintenance ecosystem.

A potential downside of adopting data-driven preventive maintenance is the shift in required skills for technicians. While fewer manual inspections mean some traditional technician roles might become redundant, the new system demands technicians become proficient in computer use, data interpretation, and accurately following detailed digital instructions. Technicians accustomed to traditional hands-on roles might find this transition challenging, highlighting a clear need for retraining and reskilling programs. Additionally, reliance on AI guidance may inadvertently lead to deskilling if technicians lose the ability to troubleshoot independently should the technology fail or overlook issues. [36]

4.3 Expert design

Lift consultants currently use ISO guidance, calculations and simulations to design lift systems that suit the building. An expert design system would do this automatically but lift consultancy is not at risk from the expert system. A lift consultant's skill is knowing what the results of an analysis mean and feeding back to an architect or structural engineer what changes need to be made. An expert design system will improve the reliability and consistency within the lift consultancy industry as all consultants will be applying the same logical rules.

In the early days of any complex expert system, experts will disagree with some edge case decisions the system produces. Feedback from expert lift consultants is essential for improving an expert system's decision-making process.

5 CONCLUSION

AI will impact the lift industry and change the way work is done. This does not necessarily mean fewer jobs, but it will mean different jobs.

In some cases, AI will remove the tedious aspects of the job allowing humans to focus on the complex aspects, such as with lift consultants. In other cases, AI will remove the skilful element leaving humans to do the muscle work, such as with technicians. Without appropriate governance, more data and analytics could result in unethical surveillance or advertising. As dispatching becomes more powerful, prioritising parameters becomes an ethical dilemma. This dilemma could be handed to the building manager by giving them the power to change prioritisation. However, one could argue that manufacturers should take responsibility for the dispatcher and not allow building owners to put money before the environment.

The industry has an ethical responsibility to care for its workers and passengers as well as the environment. As AI pervades the industry, those responsible for making the decisions should put the interests of people over the interests of profit.

6 REFERENCES

- [1] R. Peters, "Elevator Dispatching," *Elevcon*, no. 20, pp. 125-138, 2014.
- [2] W. C. Z. Deven, "Fuzzy control of group elevators," *IEEE TENCON*, 1993.

- [3] S. Kubo, S. Nakai, N. Imasaki and T. Yashitsugu, "Elevator Group Control System with a Fuzzy Neural Network Model," 1995.
- [4] C. Imrak and G. Barney, "Application of Neural Networks on Traffic Control," 1998.
- [5] B. Powell, D. Sirag and B. Whitehall, "Artificial Neural Networks in Elevator Dispatching," 2000.
- [6] L. Cao, S. Zhou and S. Yang, "Elevator Group Dynamic Dispatching System Based on Artificial Intelligent Theory," *International Conference on Intelligent Computation Technology and Automation*, 2008.
- [7] Y. Ai-rong, C. Lei and H. Yi-hui, "Research on elevator group control system based on the fuzzy neural network," *International Conference on Computer Application and System Modeling*, 2010.
- [8] L. Yu, J. Zhou, S. Mabu, K. Hirasawa and J. Hu, "A Double-deck Elevator Group Supervisory Control System with Destination Floor Guidance System using Genetic Network Programming," *SICE-ICASE International Joint Conference*, 2006.
- [9] J. Sorsa and M. Siikonen, "Double-deck destination control system," *Elevcon*, no. 16, pp. 318-327, 2006.
- [10] J. Zhou, L. Yu, S. Mabu, K. Hirasawa and J. Hu, "Double-Deck Elevator Systems using Genetic Network Programming with Reinforcement Learning," *IEEE*, 2007.
- [11] R. Basagoiti, M. Beamurgia, R. Peters and S. Kaczmarczyk, "Passenger flow pattern learning based on trip counting in lift systems combined with real-time information," *Symposium on Lift and Escalator Technologies*, no. 3, 2013.
- [12] R. Peters, "The Global Dispatcher," Northampton, 2023.
- [13] S. Kawano, T. Yuminaka and N. Kobayashi, "Remote and intelligent diagnostic system for elevators incorporating preventive maintenance," *Elevator World*, 1994.
- [14] R. Smith, "The Internet of Things, Big Data, Machine Learning, and the Lift & Escalator Industry," *Symposium on Lift & Escalator Technologies*, no. 5, 2015.
- [15] B. Langham, "How Current Technology Trends are Empowering Us All to Drive," *Symposium on Lift & Escalator Technologies*, no. 6, 2016.
- [16] X. Ma, L. Chengkai, K. Ng and H. Tan, "An Internet of Things based lift predictive," *Smart Cities*, pp. 17-23, 2021.
- [17] S. Kaczmarczyk, R. Smith and M. Gizicki, "Vibration Signature and the Application of Intelligent Pattern Recognition in Detection and Classification of Damage in Automatic

- Power Operated Lift Doors,” *Symposium on Lift & Escalator Technologies*, no. 13, 2022.
- [18] M. Gizicki, S. Kaczmarczyk and R. Smith, “Classification and Recognition of Roller Bearing Damage in Lift Installations Using Supervised Machine Learning and Vibration Analysis,” *Symposium on Lift and Escalator Technologies*, vol. 14, 2023.
- [19] R. Smith, “The Effect of Artificial Intelligence on Service Operations and Service,” *Symposium on Lift & Escalator Technologies*, no. 13, 2022.
- [20] M. Seyyedi, A. Candaş and C. İmrak, “Artificial Intelligence Embedded Image Process-Based Fatigue Life,” Kettering, 2024.
- [21] B. Khaleghi, A. Khamis and F. Karray, *Multisensor Data Fusion a Data Centric Review of the State-of-the-Art and Overview of Emerging Trends*, Taylor & Francis Group, 2015.
- [22] D. Smans, “Modelling Failure Detection of Lift Doors Through Sensor Fusion,” Kettering, 2024.
- [23] M. Siikonen and M. Kaakinen, “Using Artificial Intelligence to Improve Passenger Service Quality,” 1993.
- [24] M. Siikonen, “Elevator Group Control with Artificial Intelligence,” *Helsinki University of Technology*, 1997.
- [25] A. So, J. Beebe, W. Chan and S. Liu, “Elevator Traffic Pattern Recognition by Artificial Neural Network,” 1995.
- [26] M. Guidotti, “Smarter Buildings: IoT-enhanced Traffic Analysis Embedded in Lift,” *Symposium on Lift and Escalator Technologies*, vol. 14, 2023.
- [27] L. Al-Sharif, *New Concepts in Lift Traffic Analysis: The Inverse S-P (I-S-P) Method*, 4 ed., Amsterdam: Elevator Technology, 1992.
- [28] L. Al-Sharif, R. Peters and M. Appleby, “Enhancing the I-S-P Method (Inverse Stops-Passengers) Using the Monte Carlo Simulation Method,” Northampton, 2022.
- [29] L. Al-Sharif, R. Peters, M. Appleby and T. Ghaben, “Estimating the Traffic Mix in a Building by Analysing the Stops Data per,” Kettering, 2024.
- [30] ISO, “iso.org,” 2020. [Online]. Available: <https://www.iso.org/standard/73084.html>.
- [31] CIBSE, *CIBSE Guide D: Transportation systems in buildings*, London: CIBSE, 2020.
- [32] R. Prowse, T. Thomson and D. Howells, “Design and Control of Lift Systems Using Expert Systems and Traffic Sensing,” *Elevcon*, no. 4, pp. 219-226, 1992.

- [33] R. Peters and S. Dean, “Expert Systems for Lift Traffic Design,” *Symposium on Lift & Escalator Technologies*, no. 9, 2018.
- [34] N. Tolosana, E. Larrodé, J. Cuartero, A. Miravete, J. Calvo and L. Castejón, “Application of Artificial Neural Networks on Vertical Traffic Simulation,” *University of Zaragoza*, 1998.
- [35] C. Bird, R. Peters, E. Evans and S. Gerstenmeyer, “Your Lift Journey – How Long Will You Wait?,” *Proceedings of the 6th Symposium on Lift and Escalator Technologies*, 2016.
- [36] L. Bainbridge, “Ironies of automation,” *Automatica*, vol. 19, no. 6, pp. 775-779, 1983.
- [37] R. Peters, “The Global Dispatcher,” *Symposium on Lift and Escalator Technologies*, vol. 14, 2023.
- [38] R. Smith and R. Peters, “ETD algorithm with destination dispatch and booster options,” *Elevcon*, no. 12, pp. 247-257, 2002.
- [39] L. Yu, S. Mabu, T. Zhang and K. Hirasawa, “A study on energy consumption of elevator group supervisory control systems using genetic network programming,” *IEEE International Conference on Systems, Man, and Cybernetics*, 2009.
- [40] J. Pommereul, “Improving maintenance strategies of elevators and escalators with condition monitoring,” *Elevcon*, no. 18, pp. 296-305, 2010.
- [41] Y. Hu, “Application of Artificial Intelligence, Big Data and Cloud Computing in Optimizing Elevator Safety Performance,” *IEEE International Conference on Electrical Engineering, Big Data and Algorithms*, no. 2, 2023.

7 BIOGRAPHICAL DETAILS



Matthew Appleby is a software engineer at Peters Research Ltd. He is involved in project managing the new Elevate Online and leads front-end development. He joined Peters Research in 2019 and graduated with a first-class (Hons) degree in Software Development in 2024.