Classification and Recognition of Roller Bearing Damage in Lift Installations Using Supervised Machine Learning and Vibration Analysis

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Abstract. The resilience of rotating components, specifically traction sheaves and diverter pulleys in lift installations, is of paramount importance. However, these components frequently undergo fatigue failure due to their exposure to intense cyclic and dynamic loading conditions. Traditional methods for estimating bearing life, which show insufficiency in adapting to the dynamic operating conditions of lifts (such as variable load, speed, and direction), often fail to anticipate these breakdowns. An experimental laboratory rig comprising a rotating disk-shaft assembly with intentionally damaged components emulating real-world scenarios has been designed to address this challenge. Vibration data, representative of actual operational conditions, were systematically captured using accelerometers. This data was then leveraged to extract salient vibration features, which served as inputs to train artificial neural network (ANN) models within a supervised machine learning framework. The trained models have shown the capacity to identify and categorise damage patterns, thereby enabling a comprehensive understanding of fatigue failure mechanisms in these systems. The findings from this research demonstrate the potential for developing robust and efficient condition monitoring methodologies, which could significantly enhance both the longevity and safety of lift installations.

1 INTRODUCTION

The longevity and dependability of mechanical components within lift installations, particularly rotating elements such as traction sheaves and diverter pulleys, are paramount in maintaining the integrity of these systems (see Fig. 1). These components are subjected to vigorous cyclic and dynamic loading conditions, making them particularly vulnerable to fatigue failure – a prevailing challenge within the lift industry [1], [2]. Traditional prediction methods for bearing life have demonstrated limitations due to their inability to adjust to the diverse operating conditions that lifts typically experience [3]. As a result, these methods often fall short of effectively anticipating and preventing component failures. Given their direct implications on lift operations' safety and maintenance regimes' economic efficiency, the need for early identification and robust management of fatigue failure is critical.

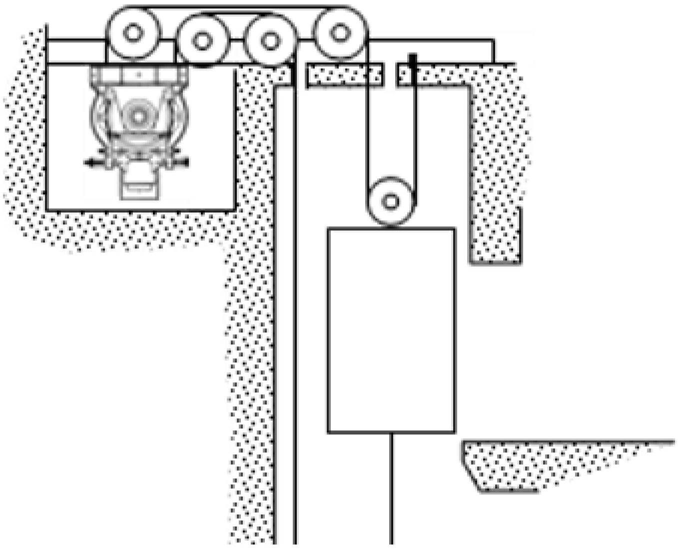


Figure 1 Inverted gearless lift machine arrangement.

Over the past decade, advancements in artificial intelligence (AI) have instigated significant transformations in maintenance procedures across various industries, with the lift industry no exception. AI technologies, particularly neural networks, have exhibited considerable potential in enhancing predictive maintenance strategies [4]. This capability to detect precursors of impending failure well in advance provides an opportunity for timely preventative action, thus offering substantial cost savings through minimising downtime and extending component lifespan.

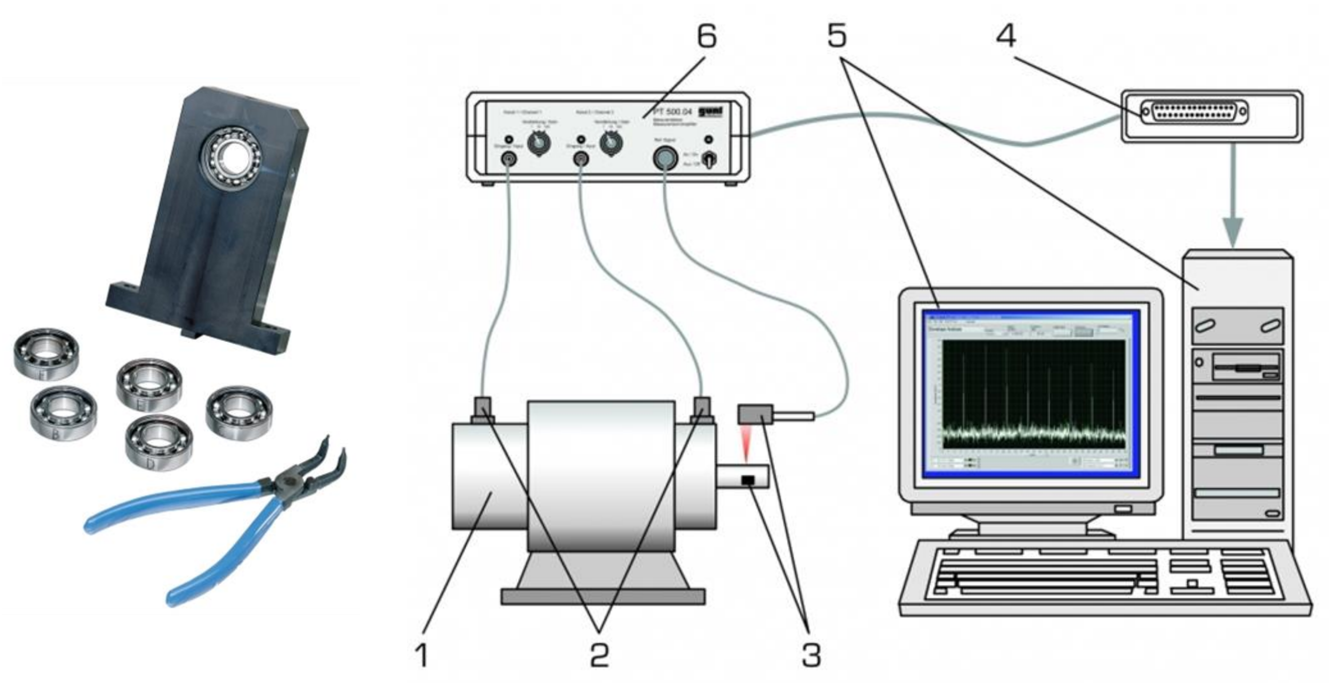
Figure 2 Experimental laboratory rig

To further investigate the potential of AI in combating component failure, the researchers developed a bespoke experimental rig (see Fig. 2). This rig encompasses a rotating shaft assembly held between two bearings and driven by a motor, mirroring real-world operating conditions. The shaft assembly was intentionally designed with both an undamaged state (Class "A") and various damaged states (Classes "B" through "F") to allow systematic analysis of different potential failure scenarios. These damage states were carefully modelled to include an unbalanced shaft, inner bearing ring damage, rolling element damage, compound damage (including outer ring roller damage), and severe bearing damage.

Equipped with accelerometers, the rig was utilised to gather vibration data, which was converted into wav files. The use of the MATLAB software platform for data processing facilitated the extraction of salient vibration features which correspond to different damage states. These features served as critical inputs for training an artificial neural network, forming the foundation of a comprehensive machine learning-based approach to condition monitoring.

Upon the training phase's completion, the neural network's performance was rigorously evaluated using new vibration data. The network's accuracy in damage classification is a crucial metric in assessing the effectiveness and reliability of this AI-based predictive maintenance strategy [5]. With a high degree of prediction accuracy, this methodology has the potential to significantly improve the way lift installations are maintained, markedly enhancing their lifespan and operational safety. Moreover, the wider implications of this research may provide a blueprint for AI-based maintenance strategies in other industries facing similar challenges related to fatigue failure and dynamic loading conditions.

2 EXPERIMENTAL APPARATUS AND DATA ACQUISITION



1 vibrating machinery, 2 acceleration sensors, 3 shaft with reference sensor, 4 USB box, 5 PC , 6 amplifier / filter

Figure 1 Experimental setup

The experiment was conducted using a bespoke testing rig, comprised of a driving motor, a shaft rotationally suspended by two roller bearings, and a flywheel (see Fig. 3). The analogue accelerometers were attached strategically on the shaft for precise vibrational acceleration measurements during operation.

The raw analogue data from the accelerometers were transduced into digital signals via a high-resolution analogue-to-digital converter (ADC). The integrity of the original signals was preserved by saving the digitised data in the .wav format, noted for its lossless properties.

Leveraging the bearings' interchangeability, seeded faults were introduced into the system to generate data for diverse damage classes. An unbalanced shaft state was induced by adding non-symmetric weight to the flywheel. In total, six damage classes were established and recorded for comprehensive analysis.

3 SIGNAL PROCESSING AND NEURAL NETWORK MODEL SELECTION

Upon examination of the data in MATLAB's Signal Analyzer [6], it was determined that all signals necessitated standardisation, smoothing, and centring. A notable peak appeared in the power spectrum around 4.1 kHz, likely attributed to the accelerometer's construction (see Fig. 4). To eliminate any influence on the subsequent results, a low-pass filter with a cut-off at 3.5 kHz was introduced.

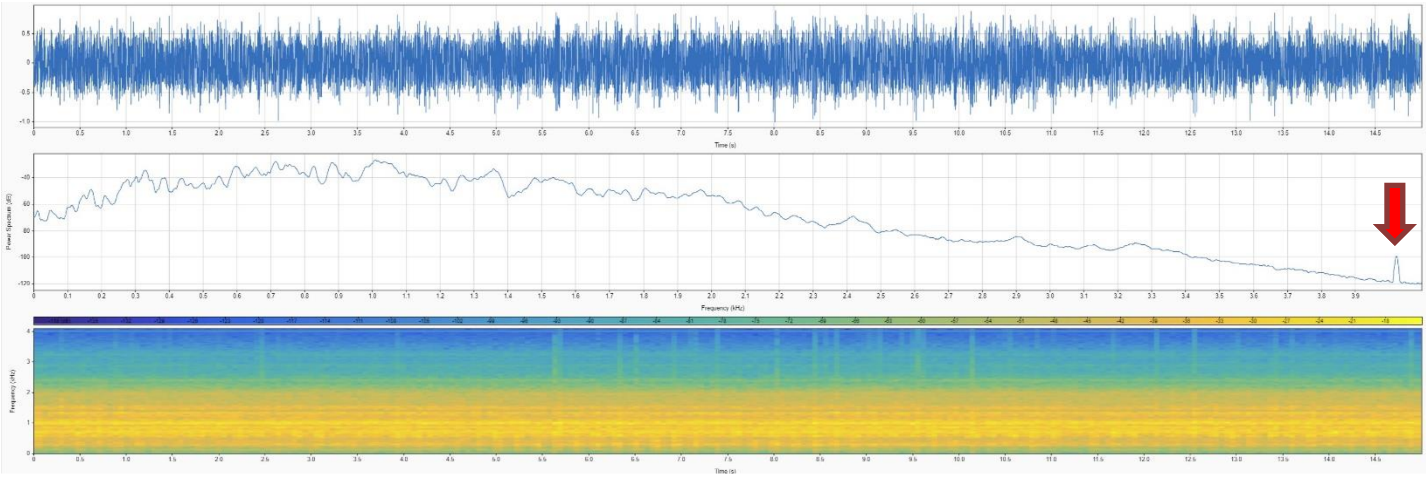


Figure 3 Signal Analyzer - Data Evaluation

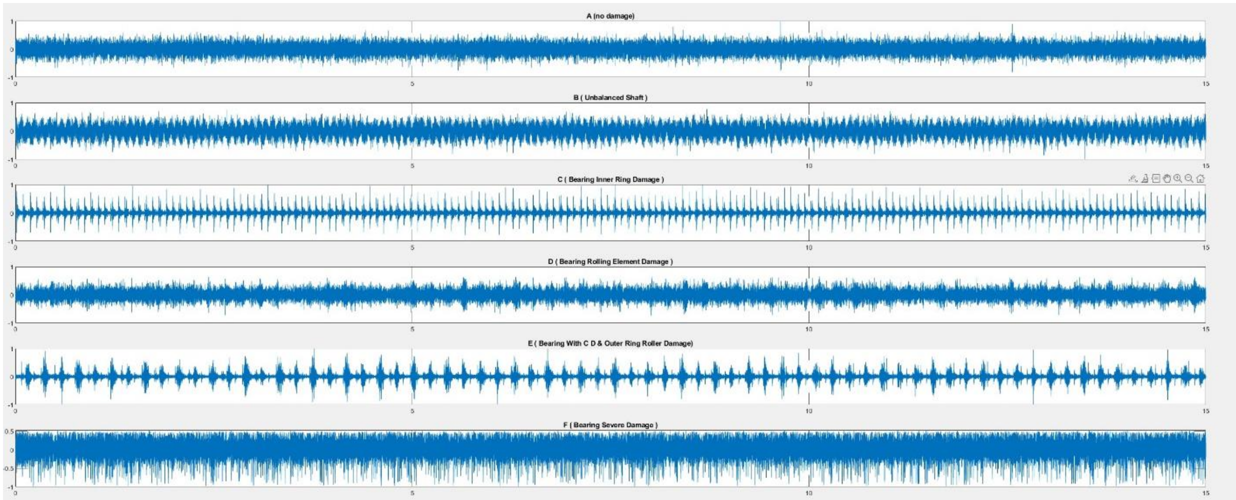


Figure 2 Six Damage Classes Signal

After pre-processing the entire collected signal data (see Fig. 5), the investigation turned towards selecting a suitable neural network model. Multiple models underwent rigorous testing, and their performance is summarised below:

- MATLAB's nnprtool app: The raw time datasets underwent pre-processing and normalisation, followed by post-processing to generate spectrograms. Subsequently, the cepstrogram's real coefficients were computed and employed as features for the Neural Network Pattern Recognition (NNPR) algorithm [7]. This process resulted in a uniquely processed Vibration Signature for each instance, contributing to the NNPR's intelligent pattern recognition capabilities. The analysis revealed that out of six classes, five were predicted with 100% accuracy. However, the 'no damage' class demonstrated a misclassification rate of 23.1% (see

Fig. 6). While these results were satisfactory, the team proceeded with the exploration of alternative models to enhance the classification accuracy further.

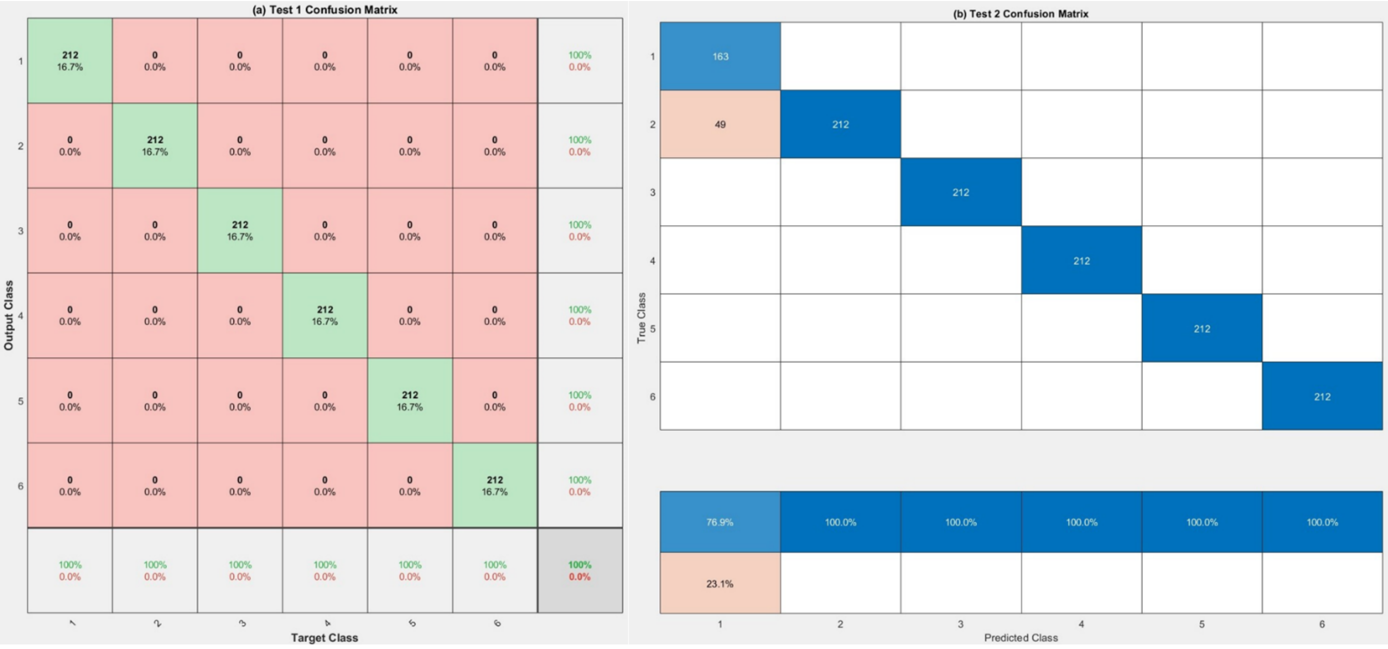


Figure 4 NNPR tool results: training and test confusion matrices

- MATLAB's feedforward network [8]: The identical set matrices as those used in nnprtool were employed. This model, however, facilitated the use of multiple neuron layers for training. Furthermore, retraining was undertaken to augment the classification accuracy of novel test data. For the feedforwardnet model, five out of six classes were correctly predicted. The 'no damage' class, though, had a misclassification rate of 35.8% initially and 31.6% after retraining (see Fig. 7). To improve these results, the team decided that more data work was needed.

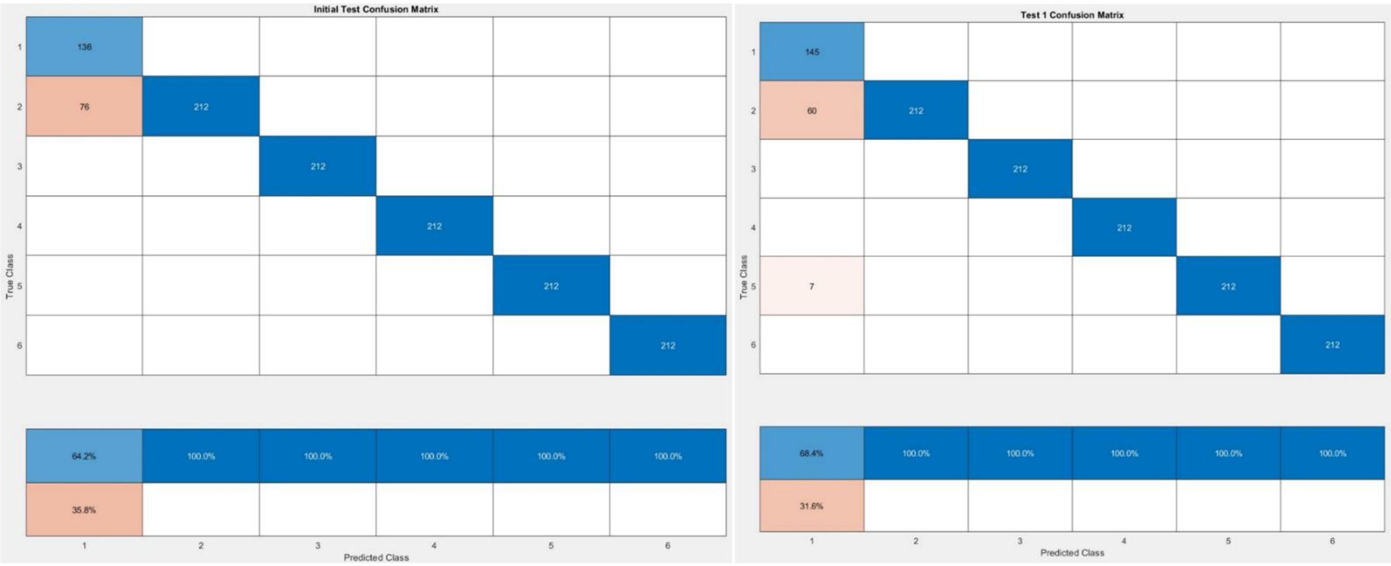


Figure 5 Feedforward net - Training and Retraining Test results

In pursuit of a more suitable model, the team initiated a new process, starting with the creation of a datastore that would be compatible with MATLAB's Feature Designer and Classification Learner app.

Signal data was initially pre-processed as in previous models and then segmented into one-second interval records. Given the motor's approximate speed of 700 RPM, each one-second data segment represented 11.6 rotations, providing a sufficient sample set for the data store.

Automated feature extraction was conducted to generate prevalent signal features after importing the datastore into the Feature Designer [9]. An Analysis of Variance (ANOVA) was subsequently performed to rank these features, with ten being classified as significant (see Fig. 8). Nevertheless, all features were exported to the Classification Learner app [10] for further analysis.

Figure 7 Feature Designer - Automated Feature extraction ANOVA ranking.

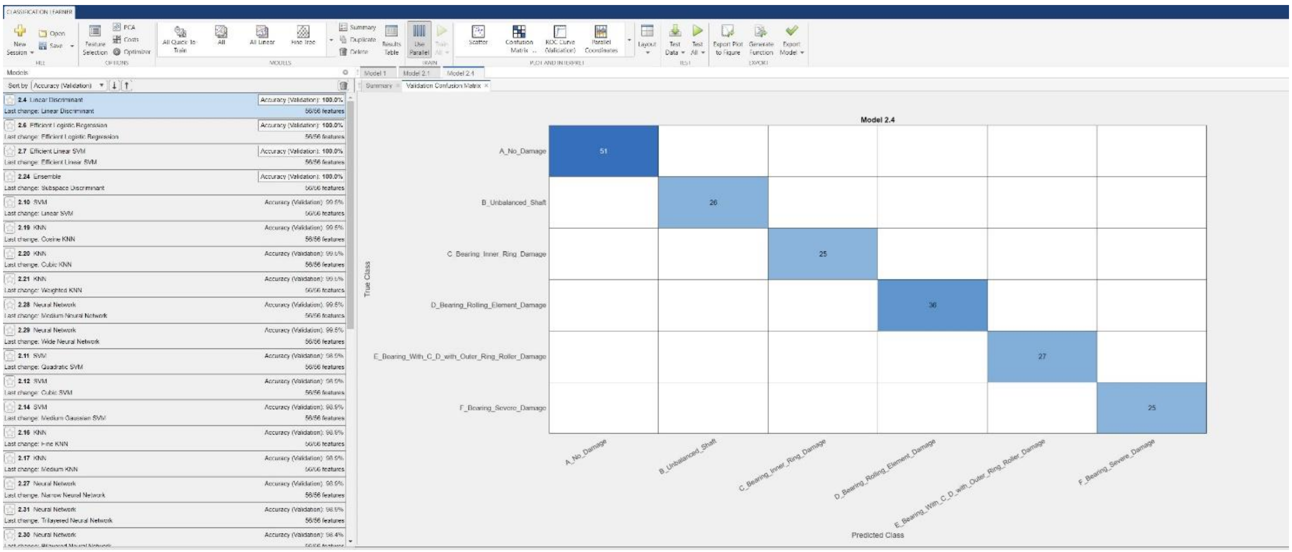


Figure 6 Classification Learner app - Training and Testing Results

Utilising the Classification Learner app, all accessible models were trained using the exported features from the Feature Designer. These models were then tested on 15% of the imported data for validation.

Remarkably, four models—Linear Discriminant, Efficient Logistic Regression, Efficient Linear SVM, and Subspace Discriminant—achieved 100% accuracy in predicting damage classification (see Fig. 9). Each of these models, exhibiting exceptional predictive performance, can hence be utilised for future measurements to anticipate damage classification reliably.

4 CONCLUSION

The research showcases the efficacy of artificial neural networks in detecting and predicting damage in crucial lift components, especially rotating shafts, pulleys and bearings. After training, the model consistently demonstrated high accuracy in damage classification, with values exceeding 80% and even reaching 100% in some cases.

The model requires additional development and broader data inputs from various lift systems for real-world applications. This strategy will likely enhance the model's predictive accuracy.

Integrating the model with MATLAB's Predictive Maintenance Toolbox can further improve its predictive capabilities. This software suite provides advanced tools for condition monitoring and failure prediction, leading to accurate failure time estimates and facilitating proactive maintenance.

In conclusion, the study presents a potential shift towards proactive maintenance strategies in the lift industry, focusing on rotating and other components. This move, aided by AI, promises more reliable and safer lift systems, marking a promising direction for future research and practical applications.

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BIOGRAPHICAL DETAILS

Mateusz Gizicki has a bachelor's degree in mechanical engineering from the University of Northampton and is currently working towards achieving his doctorate in the area of multi-physics and computational fluid dynamics. He is a member of the Institution of Mechanical Engineers. He has experience in research and development in the industry environment as well as academia. In addition, he has recently completed the Knowledge Transfer Partnership project, which combined management skills with complete product development as an associate.

Dr Stefan Kaczmarczyk is Professor of Applied Mechanics and Postgraduate Programme Leader for Lift Engineering at the University of Northampton, UK. His expertise is in the area of applied dynamics and vibration with particular applications to vertical transportation and material handling systems. He has published over 100 journal and international conference papers in this field. He is a Chartered Engineer, a Fellow of the Institution of Mechanical Engineers, and a Fellow of the Higher Education Academy

Dr Rory Smith has over 50 years of experience in all aspects of the lift industry including sales, installation, maintenance, manufacturing, engineering, research & development. He has worked for ThyssenKrupp Elevator for the last 24 years. Prior to becoming involved in ThyssenKrupp's Internet of Things, he was Operations Director at ThyssenKrupp Elevator Middle East. His scientific interests include: operations management, high rise–high speed technology, ride quality, traffic analysis, and dispatching. To date, he has been awarded numerous patents in these areas and has many pending patents.