Condition Monitoring for Major Airport Baggage Systems

Abstract

Purpose: The purpose of this paper is to develop a contribution to knowledge that adds to the empirical evidence of preventative condition-based maintenance and challenges the assumption that the overall performance of a system is limited by the performance of current assets without costly capital investment.

Methodology: The empirical, experimental approach, technical action research (TAR), was designed to study a major Middle-Eastern airport baggage handling operation as an illustrative case study, where a predictive maintenance prototype station was installed to monitor the condition of a highly complex system of static and moving assets.

Findings. This paper provides evidence that the performance frontier for airport baggage handling systems can be 'bettered' by using automated dynamic condition monitoring of the vibration and digital image data on baggage trays as they pass a service station. The issue of asset failure in a complex, tightly coupled, and high speed operating environment is resolved through low-end innovation that combines advanced technology with existing low-cost hardware.

Originality/Value: The originality derives from the application of existing hardware with the combination of Edge and Cloud computing software through architectural innovation resulting in adaptations to an existing baggage handling system within the context of a time-critical logistics system.

Keywords: IoT, Condition-based Monitoring, Predictive maintenance, Edge computing, IoT, Technical Action Research, Theory of Performance Frontiers,

Case Study

Introduction

With Industry 4.0 and the increasing adoption of digitalisation, airports are continually exploring ways to enhance process cost and efficiency, as well as asset availability and reliability, while passenger volumes are rising. In recent years, e-ticketing, self-check-in, bag drop-off, automated border control systems, and automated self-service barriers have been installed to improve airport passenger logistics (Price and Forest, 2016; Haddad et al., 2017). While passenger-facing systems have improved, the airport 'back office' of baggage-handling systems (BHS), has lagged in digitalisation. As a result, the total airport logistics system has yet to be optimised. The industry is at the point in the innovation 'S' curve to realise the benefits of such pilot projects (Rogers, 1995).

Performance of less than 100% on-demand BHS availability can cause significant flight delays and complaints. Past practice has been to install redundant and bypass conveyor lines wherever there is sufficient space in the baggage hall (Scholing, 2014). Such excess infrastructure is costly and also needs to be maintained. A single failure in one part of the system causes an instant back-log, and eliminating unplanned system downtime is a prerogative. Redundancy is also incorporated for other BHS equipment, such as baggage screening machines, hoists, sorters, so that if one device fails or needs to be taken out of service for maintenance, there are second, third or more alternative devices that can take over without any significant negative impact on the overall operation and customer satisfaction. The significant limitations of a "redundancy strategy" include excessive space requirements and extra cost, both of which are not always available. At many airports, space in baggage halls is insufficient, and extending buildings is not a feasible option (Lin and Huang, 2015). For some airports, there are systems in which redundancy cannot be installed, which means that a single failure, in a time-critical process, can have an enormously negative impact on operations and customer service (Scholing, 2014). The imperative for airports is to modernise their systems and processes through the adoption of the latest logistics technology to handle the continually rising number of baggage items per square metre of airport space cost-effectively and with higher levels of proactive control. Such systems require well-organised preventive maintenance, which, due to the sheer number of assets on-site, is challenging and costly to plan and process. Failure to prevent breakdowns in an environment in which redundancy is limited, or not an option, often results in expensive repairs, missed baggage, and extra costs for customer baggage repatriation. To overcome these challenges, airports are moving towards the implementation of more modern monitoring systems that are already operational in other industries, such as condition-based and predictive maintenance.

This paper contributes to the academic understanding of effective maintenance management practice in a highly complex and time-critical operational environment where one 'moving asset' interacts closely with another 'moving asset.' Traditional research has focused on the effective maintenance of static assets (such as production machinery) or single moving assets (such as haulage vehicles). The context of maintaining dual moving assets is unusual and, in a time-critical logistics system, involves a significant number of assets (infrastructure and moving assets) and complicated wear patterns of sub-assets (such as bearings, shafts, belts). The chosen context of this study is 'on-demand' airport baggage handling systems, which are highly critical assets that support the movement of mass numbers of passengers in short periods where there are significant penalty charges for any delays or losses for suboptimal performance. The paper explores the context between traditional maintenance practices and modern technology that supports purpose-built service systems. The case study presented here utilises existing assets that have been adapted using monitoring devices and high levels of computing capability to move the asset frontier (Schmenner and Swink, 1998) to support operational performance improvements.

The study aims to develop a contribution to knowledge that adds to the empirical evidence of preventative condition-based maintenance and challenges the assumption that the overall performance of a system is limited by the performance of current assets without costly capital investment.

To do this, we identify the opportunities and benefits that can be realised from real-time data processing to control complex and performance-critical operating systems through architectural innovation of existing assets to form new processes (Henderson and Clark, 1990; Galunic and Eisenhardt, 2001).

In addressing the study's aim, the authors use the lens of performance frontiers to explore whether dynamic data processing can be used in conjunction with existing electro-mechanical monitoring devices and adaptations to existing processes to result in higher system performance. This approach involves real-time data management and low-end disruptive innovations rather than new hardware and software to achieve optimal operational performance (Christensen 1997). The paper is not claiming that any of the individual elements of condition-based maintenance in this study are innovative; a skilled technician can differentiate between a tray that needs maintenance through sight and sound **but not at speeds above 10m/s in a system that is running 24/7**.

The originality of this study is not in the applications of existing technology itself but in the approach of combining existing hardware with new advanced technology and software in different ways through architectural innovation (Henderson and Clark, 1990; Galunic and Eisenhardt, 2001) to solve practical, business problems. This paper demonstrates how applications from the Internet of Things (IoT) can be applied in a relatively simple, timely, and cost-effective manner, thus enabling BHS companies to move forward to achieve the benefits offered by Industry 4.0 quickly and easily.

To achieve the aim of the study, we anchor this research on the *Theory of Performance Frontiers* (Schmenner and Swink, 1998). Using this theory, the authors explain how to push the performance frontiers of airport logistics systems to keep pace with increasing passenger and baggage traffic per square metre of airport space.

Schmenner and Swink (1998 p. 108, citing Samuelson, 1947) define a performance frontier as the *'maximum output that can be produced from a given set of inputs, given technical considerations*,' which represents the maximum performance under optimal asset capability and utilisation (Boer et al., 2015). Although developed for Operations Management, the theory of performance frontiers suits manufacturing maintenance or service businesses.

The theory of performance frontiers identifies two frontiers of performance improvement, the *Operating Frontier* and the *Asset Frontier*. The operating frontier is the maximum output for a given set of operating choices utilising the current assets. The operating performance can be improved by adopting new policies, such as Lean or Six Sigma, through 'betterment,' a term used by Schmenner and Swink (1998), or by the laws of cumulative capabilities (Ferdows and De Meyer, 1990; Vastag, 2000). Improving operating performance moves the operating frontier closer to the asset frontier and changes the shape of the operating space (Figure 1); the asset frontier remains the ultimate boundary for performance (Holweg et al., 2018).

Take in Figure 1: Performance Frontiers (adapted from Schmenner and Swink, 1998)

Inherent trade-offs exist in theory between performance and cost and implying that improvement in one dimension can only be at the expense of the other. As improvement increases and the operating frontier moves towards the asset frontier, some fundamental laws come into play, such as the law of diminishing returns (Samuelson and Nordhaus, 2001). Schmenner and Swink(1998) argue that this can be reconciled through cumulative capabilities, described by the sandcone model of Ferdows and De Meyer (1990) and the law of contiguity and cumulative capabilities (Baum, 1973), which states that we can measure all consequences of interactions and activities on a common scale, called 'value.' As such, performance improvement can be made in multiple dimensions, but the rate is subject to diminishing returns as the operating performance moves closer to the asset frontier.

According to Vasteg (2000), the theory of performance frontiers described by Schmenner and Swink (1998) requires clarification. In the original paper, there were no arrows on the axes, but it is assumed that both increase and that cost refers to investment, which, in reality, forms step changes rather than a curve.

It is considered that the 'asset frontier' is the glass ceiling in the performance frontier (Holweg et al., 2018), as it is often cost-prohibitive to improve assets. In this study, we demonstrate that, as technology has improved with the introduction of new digital platforms, the solution's investment cost has not continued to increase exponentially; instead, the cost has decreased relative to technology advancement. Solutions that were not previously financially viable are now affordable, allowing asset utilisation and capability to reach another level. This paper challenges the assumptions that the ‘asset frontier’ is a glass ceiling to performance improvement and demonstrates that it is a function of the maintenance and ‘betterment’ of the assets and, when this utilises the opportunities of the IoT and new technologies, the asset frontier can also be moved forward. In doing this, we aim to contribute to the theory of performance frontiers using an illustrative BHS case study operating at a major Middle Eastern airport hub.

The remainder of this paper commences with introducing the *practical problem* this research addresses, and then we summarise the *technologies* underpinning the proposed solution. The reason for this is two-fold: First, to give a broad understanding of how we aim to identify what opportunities and benefits can be realised from real-time data processing to control complex and performance-critical operating systems. Second, whether dynamic data processing can be used in conjunction with existing electro-mechanical monitoring devices and adaptations to existing processes to result in higher system performance. Finally, we discuss the results from a pilot trial and implementation of a new baggage handling monitoring system at the purposively selected exploratory case study (Siggelkow, 2007) to help the reader imagine how the conceptual argument applies in practice.

Context of the Practical Problems in Airport Baggage Handling Systems

The first automated airport BHS system was installed in Frankfurt in the 1970s, where, instead of transporting baggage on a conveyor belt, bags were transported in trays driven by conveyors (Jeffcoate, 1997). Similar airport systems transported bags in vehicles on tracks. Both systems are classified as Direct Coded Vehicle (DCV) systems. The advantage of DCV systems is that every tray, or vehicle, has a hardcoded identification number where baggage related data can be stored. The DCV transport speed is more than 10m/s, which poses a major technological challenge. Currently, major BHS airport hub systems are designed with a combination of belt and DCV conveyor technology. From the check-in, bags are conveyed into the system and, after the security screening, they are subsequently loaded onto DCV trays.

DCV transport trays are robust, and the only wearing parts are two polymer-coated bearings and tray inlays. Every tray has a front and a rear guide roller, which wears over time, resulting in diameter loss. Excessive wear, or diameter loss, results in rail and tray damage that creates a high risk of DCV derailment and system downtime.

A major airport hub has more than 20,000 trays circulating on up to 200 km of conveyors travelling at speeds of up to 10 m/s in systems that continuously operate 24/7 with little tolerance of downtime. Hence the risk of failure is high, and the cost of failure, at over $100 per bag (Scholing, 2014), can exceed $1m in the case of a DCV derailment. Reliability and maintenance of the conveyor systems are the most critical factors that affect the availability of the system (Alsyouf *et al.,* 2015).

A cost-effective condition-based monitoring solution is required to take airport baggage systems into the next generation. Achieving this requires identifying what opportunities and benefits can be realised from real-time data processing to control complex and performance-critical operating systems and whether dynamic data processing can be used in conjunction with existing electro-mechanical monitoring devices to achieve higher system performance.

To solve the practical engineering problem, that this research addresses, we start by discussing, in more detail, the technical developments that are utilised as a part of a conditioned-based maintenance system capable of reacting to operating systems where mobile assets move at speeds over 10m/s. We discuss why it is essential to develop a predictive, condition-based maintenance system, and then we discuss the use of vibration techniques and digital image processing to replicate the auditory and visual skills of an experienced maintenance technician. We then explore how these monitoring techniques can be used in real-time at high speeds through advanced computing and technological innovations.

Background Research in Underpinning Technologies

Condition-based Maintenance

To effectively minimise system downtime and to avoid breakdowns, a maintenance strategy must include asset condition monitoring in real-time so that its remaining life can be estimated, and a proactive maintenance intervention can be initiated (Jardine *et al*., 2006, Yam *et al.,* 2001). Predictive maintenance systems comprise two forms of proactive maintenance designed to reduce downtime. These are reliability centred maintenance (RCM) and condition-based maintenance (CBM). They differ primarily in how they are performed and how maintenance requirements are measured (Fraser, 2014).

CBM is defined as the use of monitoring techniques to diagnose or predict failure (Veldman *et al.,* 2011). Thus, CBM relies on exact measurements and calculations in addition to the sensor measurements of temperature, vibration, noise, and is performed when needed based on the calculations (Mobley and Keith, 2002).

CBM comprises three steps (Jardine *et al.,* 2006):

1. Data Acquisition – obtaining data based on the health of the system
2. Data Processing – handling and analysing the data, or signals, for better understanding of the heath of the system
3. Maintenance Decision Making – recommending effective maintenance actions.

There are two important elements to CBM, diagnostics and prognostics (Jardine, Lin and Banjevic, 2006). Diagnostics is the detection, isolation and identification of failure that occurs post-event. Prognostics, on the other hand, is prior-event and is based on the detection of faults before they occur based on information on trends and other warning signals. There is abundant literature on diagnostics, but the literature on prognostics is much more limited (Jardine, Lin and Banjevic, 2006).

Researchers have noted that predictive maintenance strategies offer economic advantages over preventative 'time-based', or reactive 'run-to-failure' maintenance because the requirement is based on actuality, rather than on estimates of condition and performance (Tickoo et al., 2010). However, the initial costs of CBM can be high due to investment in sensors and training, and, also, there are on-going sensor maintenance costs to consider. Nevertheless, in most time-critical industries, CBM is the best available strategy for preventing unexpected and costly system downtime (Rao, 1996; Carden and Fanning, 2004).

Typical conditions, measured and monitored by sensors in CBM systems, are temperature, moisture, noise, vibration, oil analysis, and lubrication monitoring (Jardine, Lin and Banjevic, 2006). According to Veldman *et al.,* (2011), there are 4 types of CBM. Type I and Type II are based on analytical modelling where measurements are analysed by expert systems and equipment is only taken out of service when evidence exists that deterioration has occurred. Type III and Type IV are primarily predictive and based on statistical modelling based on process or failure data. Predictive CBM is based on the same principles as analytical CBM maintenance but involves a different method for determining requirements for specific maintenance services. The advantages of all CBM systems stem from the fact that maintenance is scheduled only when needed (Hashemian and Bean, 2011).

Commonly CBM uses acoustic and visual techniques to determine patterns of wear. In this paper, we explore *Vibration Monitoring*, which is identified by techniques that capture shock and sound waves and *Digital Image Analysis* to explore the visual condition of the assets.

Vibration Monitoring

A widely accepted tool to monitor machine operating conditions is vibration analysis. Traditional applications of vibration analysis include civil engineering (static structures) and bearings/shafts (primarily of static machinery) where sophisticated techniques for detecting gear failure or ball-bearing faults are well-established in industry (Forrester 1989; Baydar and Ball, 2001; Yam et al., 2001; Carden and Fanning, 2004; Tondon and Choudhury, 1999; Ebersbach and Peng, 2008, Rao, 2019). There are also standards defined by organisations, such as the International Standards Organization (ISO) that recommend various reference alarm levels (Yam et al., 2001).

Unwanted vibration can cause mechanical degradation and negatively impact on machine performance (Crandall, 1970). According to Carden and Fanning (2004), the focus on mechanical systems is eliminating or reducing unwanted vibration. Randall (2010) used the term 'Forced vibration' to refer to vibration in which a force is repeatedly applied to a mechanical system. Vibration on structures is commonly measured with electronic sensors called accelerometers, which convert acceleration to a voltage signal that can then be measured and analysed.

In many applications, vibration signals are smoothed using averaging functions. However, there are applications where the maximum measured vibration is of interest (Ebersbach and Peng, 2008). The approach used in this instance is peak-to-peak velocity measurement. As a particular mechanical component begins to deteriorate, the amplitude of the peaks in the vibration spectrum increases as measured by an accelerometer. Criteria for predicting component failure are developed based on vibration measurements accumulated over time (Tickoo et al. 2010).

Digital Image Analysis

Digital image processing originated in the 1960s (Belbachir, 2010). Rinner and Wolf (2008) explain that digital image technology was applied concurrently with the development of cameras for the private sector in industry. Omron entered the market with an automated inspection system in the 1980s. Omron Electronics and Imaging Technology were the pioneers in the industrial digital-image approach (Belbachir, 2010).

Although financial and practical considerations have driven the industrial application of digital image processing (Rinner and Wolf, 2008).

Many articles have been published on image processing technology applications used to inspect the quality of a product (Sturgill and Detrick, 1986; Lahajnar *et al*., 2002; Ranky, 2003; Ghita *et al.*, 2006; Patel *et al*., 2012). One example is the bottling industry, in which image recognition technology made human inspections redundant (Heyrman et al., 2005). In the bottling industry, bottles are taken out of service if they are not filled correctly or if the label is missing or misaligned. In France, the production lines of the world-famous champagne producer Moet & Chandon accurately inspect the position of closure and label, any scuffing of a bottle, and detect foreign objects and the fill heights of up to 13,000 bottles of champagne per hour (Dave and Hadia, 2015).

Processing speed and data storage have been problems in using real-time monitoring of large amounts of data in complex, time-critical, and rapidly moving industries. Isola et al. (2017) consider that the problem currently is that image recognition algorithms have improved, but with the disadvantage of producing large amounts of data (Isola *et al*., 2017). As a result, research today concentrates on IoT and connectivity capabilities (Aitkenhead *et al*., 2006; Satyanarayanan *et al*., 2015; Wilkins, 2019).

Internet of Things and Advanced Computing Capabilities

According to Botta et al. (2016), early IoT applications mostly collected data from 'Things' and sent them to the cloud for analysis. The advanced computing capabilities of 'Things' now allow complex computation to run 'on-site' where the data were captured (Botta et al. 2016). However, there is a hefty load on the server that must process data from various data-collecting devices simultaneously (Cao *et al.*, 2018). Beaty (2018) contends that the critical problem today is that even the fastest telecommunications infrastructure networks have bandwidth and security limitations.

The ability to perform advanced on-device processing and analytics is referred to as 'Edge' computing (Mach and Becvar, 2017). The network Edge is where the device, or the local network containing the device, communicates with the internet. The Edge of the network must be geographically close to the device, unlike the original cloud server, which can be very far from the devices it is communicating with (Mach and Becvar, 2017). Edge computing runs fewer processes in the cloud, and the processes run locally on programmable logic controllers (PLCs), smart cameras, computers, and other IoT devices. Edge computing is a relatively new concept that can be traced to 2014, with newly designed applications being run as part of the computation directly on the Edge, which not only reduces latency but also ensures that applications are not compromised by the limitations of network connectivity (Lin and Huang, 2015; Cao *et al.*, 2018). Edge computing limits latency because data do not have to bridge over a network to a cloud for processing (Beaty, 2018).

Lin and Huang (2015) consider that the ideal application is one in which latencies of milliseconds are required, or in which processes and analyses must run close to 'real-time.'

Additionally, many applications do not have to send data to a network as soon as they are produced. Instead, the computing system compiles the data locally and sends a string of data several times per day to the cloud for long-term storage or operational data-visualisation purposes (Lin and Huang, 2015). Many sensor-intensive industrial IoT applications find data that need to be captured, analysed, and utilised as they come in (Beaty, 2018).

The essential element is the speed of data and analysis in many industrial IoT applications. Moving computing closer to the 'Edge' of the network enables processes to analyse data in near real-time (Beaty, 2018). All these benefits of high processing speed, bandwidth optimisation, best use of storage, reduced time, and cost are achieved by controlling the dataflow into the cloud.

Summary

Monitoring asset operating conditions by measuring vibration, along with other conditions such as heat, lubrication, and oil viscosity, is a traditional approach to maintenance that harnesses sensors to capture measurable variations in the asset conditions. Similarly, conventional gray-scale digital image processing is used to monitor the physical condition of assets. Until recently, it was capturing and storing large amounts of data was limited as data processing at high speed required costly equipment. The ability to store and process large amounts of data is now more cost-effective as a result of Cloud and Edge Computing and the IoT.

The following propositions are drawn from the review:

1. The most efficient way of preventing failures is through CBM.
2. Monitoring the vibration of the moving assets can highlight carts that are failing.
3. Digital image processing can detect damaged trays and worn guide rollers.
4. Advanced computing technology enables the real-time monitoring of data.

To achieve the overall aim of the research, we explore which sensor and image processing technologies enable technical CBM solutions to be built into the BHS of a major airport hub with minimal disruption to the operation. By doing this, we explore whether existing electro-mechanical monitoring devices can be used in conjunction with adaptations to existing processes to deliver a cost-effective CBM solution that results in higher system performance. In doing this, we demonstrate that, by pushing the baggage handling asset frontier or the 'glass ceiling' of airport logistics, the overall airport system's operating performance is improved.

Research Methodology

The methodology of Technical Action Research (TAR), known for its reliability in understanding, planning, and implementing change in operations within large complex organisations (Wieringa, 2014), was adopted. TAR is a form of action research (AR) and includes a wide range of diverse analytical research methods to determine problems or deficiencies in organisations. The target is to create an efficient, continuous improvement process of learning, evaluation, and improvement (plan, implement, evaluate, then re-plan, implement, evaluate) to achieve better results. Therefore, TAR is the use of a learning process that is ideally suited to modern complex operating systems (Wieringa, 2014).

TAR usually involves multiple disciplines within an organisation and knowledge of the dynamics of organisational change is essential to inform how an operation, such as a large socio-technical system, recognises and embraces the need for change. The approach articulates the desired outcome of a change, then actively plans and implements how to achieve the desired future. Such knowledge includes an understanding of how change influences systems and affects the dynamics of the organisation (Baum *et al*., 2006). Figure 2 illustrates the TAR process adapted from Wieringa (2014).

Take in Figure 2: Technical action research process, adapted from Wieringa (2014)

Technical action researchers need a prior understanding of the corporate environment, together with a broad knowledge of organisational systems, best practice and the operational dynamics of social environments. This prior understanding should refer directly to the practical knowledge and experience such researchers bring to a project. They must, therefore, have detailed knowledge of the operations and the contribution expected to be made to the organisation's competitive strategy (Brydon-Miller *et al*., 2003).

Results generated by action research projects are incremental, moving in small steps from individual action to situation-specific theory. Projects unfold through cycles as problems and issues are discovered and addressed by members of an organisation and researchers. Enactment of the cycles of planning, taking action and evaluation can be anticipated but cannot be designed and planned in detail, nor in advance (Avison *et al*., 2001). The underlying philosophy TAR is, therefore, that the stated aims of the project lead to planning and implementing the first action, which is then evaluated through reflection and the next step in the change process is determined. The meta step (i.e. the second action) cannot be planned in detail until after the execution of the first action and learning has occurred (Koshy *et al*., 2010). TAR does not lend itself to repeatable experimentation; instead, each intervention is different from the last, and TAR does not create widespread knowledge but solves situation-specific issues that can then be generalised (Reason and Bradbury, 2006). Hence this paper is an illustrative case study.

The TAR approach can be initiated to solve an immediate problem, or to create a reflective process of progressive problem-solving among individuals working in teams, or a 'community of practice', to improve the way issues are addressed and problems solved (Coughlan and Coghlan, 2002; Denscombe, 2010). The nature of TAR helps to mitigate bias, as the research design is based on workplace ('Gemba') visits and real observations of frontline operations, in addition to iterative cycles of observing, experiment, explain and test, with a diverse team of operators and engineers who challenge assumptions.

This TAR process, outlined by Wieringa (2014) in Fig. 2, was adopted for the pilot study CBM experiments at a major airport hub in the Middle East.

Research Process and Findings

The research follows the five process steps of the TAR cycle (Wieringa, 2014) to solve the application of PdM/CBM techniques for airport baggage handling, coupled with digital technologies.

1. *Research Problem Investigation*

One of the researchers spent several weeks at a major airport hub in the Middle East, observing the tray maintenance process of the baggage handling system.

The first observation of interest was the flow of trays to the service station. Currently, trays are routed by the IT system to the tray maintenance station based on a rotational 'round-robin' periodic maintenance principle, in which the DCV tray condition is manually inspected by a service technician who then decides the appropriate service required if any. The problem with this system is that it is subjective and does not facilitate predictive maintenance and data gathering. As a result, the risk of failure and derailment is high, with consequential system downtime resulting in customer dissatisfaction and substantial financial and reputational damage.

The second observation was that the trays passing a transition point on a high-speed line generate a different noise level depending on their condition. Experienced service engineers associate this difference of noise level with the metal tray-base misalignment. This noise leads to the hypothesis that there is a relationship between the vibration generated by the passing trays at the transition point and that this vibration can be measured to indicate misaligned trays.

The third observation of interest was that there were cases in which a tray displayed signs of heavy usage with broken edges. Trays that have been used in the system for several years are regularly polluted with debris, including aircraft exhaust particles, which is considered the most likely cause of the polymer aging process. Currently, the condition of the tray is inspected manually for deterioration and damage. By photographing these using standard grey-scale cameras, the damage is visible. Based on the premise that what can be seen can be measured, we propose that digital image processing can automatically detect tray damage and conditions.

The final observation referred to the quantity dimension. With around 20,000 trays circulating within the system, up to 500 guide rollers require replacing per month, and these represent the highest usage part consumed.

We propose that finding trays that are damaged, or worn, and removing them from the system for maintenance would improve the performance of the entire BHS. Also, eliminating the need to inspect each tray, irrespective of condition manually, would improve the system's productivity. Finally, organising the tray-fleet maintenance plan to prioritise the worst-condition trays would improve the system's reliability and the maintenance cost.

2. *Research Design*

It is essential to establish a pilot test to close the research gap for new technologies (Bergaus, 2015). The BHS in a Middle East major airport hub selected for this research is in 24/7 operational use and, thus, all pilot testing is needed under controlled conditions within a sub-system built around the live operational lines to avoid any interference with live operations

The method used during the prototype phase was similar to the known methods of 'design science' and 'experimental research.' Design science research is a set of analytical techniques and perspectives for performing research on technical systems (Collector and Module, 2011). The design process is a sequence of expert activities that produce an innovative product (see Figure 3). Experimental research is a systematic and scientific approach in which the researcher manipulates one or more variables, then controls and measures any change in other variables. This approach is used to understand causal processes. The pilot tests produced data daily, which were stored in a database and used to generate statistics, initiate root-cause analysis, and facilitate prioritised maintenance planning.

Take in Figure 3: The Engineering Cycle adapted from Wieringa (2014)

A pilot tray-fleet condition-monitoring station was built on a baggage-handling DCV line with a theoretical maximum throughput of 4500 trays per hour. The average throughput, based on the real baggage volume, was measured at 800 trays per hour. This number means that the condition of about 0.6 million trays could be measured per month and the data made available. There are up to 20,000 trays in operation. The tray count in the condition-monitoring system was measured at 17,500. The condition of individual trays was measured up to 32 times per day.

The condition of the metal base was measured using an accelerometer to record shock vibration. The condition of the polymer inlay of the tray was measured using image processing technology with a camera on top of the conveyor to measure damage and pollution. Tray guide-roller condition data were captured using additional cameras facing the guide rollers underneath the conveyor and inside a Z-rail (guide-roller rail or track). Every tray was identified by a unique tray number on the RFID tag. Specific tray data were linked to the unique tray number and pre-processed before transmission to the IoT cloud-based ecosystem.

Take in Figure 4: Pilot test with Edge and Cloud Computing Technology.

The next sub-section of this paper covers the technical development of an affordable and reproducible tray-fleet condition-monitoring system that captures data on the real condition of DCV trays.

Vibration-Monitoring System

An accelerometer was used to detect shock vibration in the form of 'peak to peak' changes in empty carts' motions as they move around the conveyor system and its transition points. An empty cart of a good standard (gravitational constant) records low free vibration as it transitions across dampened conveyors: misalignment and structural damage of the cart shows as spikes with high 'peak to peak' variations. At speeds of 2.5 metres/second, this can be detected within the capability of an accelerometer. Measuring moving trays is a significant advance and large peak to peak variations identify trays that are misaligned and at high risk of damaging the infrastructure, which could lead to catastrophic failure of the whole conveyor system.

Figure 5 illustrates the relationship used to develop a condition-monitoring solution of the tray base, with the figure on the right portraying high vibration correlated with a high dB noise level for a damaged metallic tray base

Take in Figure 5: Relationship between vibration generated and metallic frame condition.

Digital-Image Monitoring System

The DCV tray conditions can vary from clean to dirty and from lightly to heavily damaged. Currently, the causes of the damage are unclear. There is a suggestion that heat and pollution could, over time, lead to the polymer hardening, causing brittle edges to break, but this is yet unproven. The required solution needs to identify the tray's condition and provide an empirical value to the level of pollution and how damaged an inlay is. The technology applied to evaluate the tray condition is based on digital image processing and sample benchmarking. The contamination detection output is a listing that enables maintenance engineers to organise the cleaning of dirty trays only.

There is no objective measure for "dirtiness"; therefore, a quantitative measure of relative colour is sufficient to enable maintenance engineers to organise cleaning based on actual conditions. A method was defined whereby a camera was mounted on top of the conveyor line to take a grey-scale image of each passing tray. The images comprise pixels that provide a value dependent on the intensity of light returned from the image. Grey-scale technology uses intensity as an 8-bit integer, offering 256 possible different shades of grey. The scale ranges from black to white, with 254 different shades of grey in-between. The mean average grey-scale of the tray inlay is a sufficient indicator of the extent or degree of surface contamination. By sorting all the data, the maintenance engineers can organise tray-inlay cleaning based on the real condition. Theoretically, over time and with rising contamination, the average tray grey-scale should decline (the darker the shade, the lower the number). This method of monitoring grey-scale enables the maintenance department to observe trends and to determine how effective cleaning protocols are and how quickly surface pollution develops.

Additionally, the tray inlay shape is rectangular with rounded edges. A new and undamaged tray inlay has a circumference of 6.18m. In pixel terms, that circumference equals 206,000 pixels. The contour of an undamaged tray inlay was stored in the camera program to act as a pattern match. The camera program calculates the circumference of such breakouts if they occur and converts the value from pixels to centimetres. The tray with the most damaged inlay can be identified by summing the circumference values of the damaged sections.

The target of this condition-monitoring solution is to enable maintenance engineers to automatically sort the entire tray fleet from the worst to the best tray-inlay condition to identify those trays affected by pollution and damage. Furthermore, this solution measures the condition of the entire tray fleet, which can be used as a key performance indicator (KPI) for the effectiveness of operations and maintenance.

Guide-Roller Condition Monitoring

Guide rollers comprise a spherical bearing coated with a friction-reducing polymer. The guide rollers wear in different ways, most commonly through the loss of diameter caused by friction wear. Another form of wear is parts or all of the polymer coating breaking off through impacts encountered at some point in the system. Modern industrial cameras have various techniques available to measure the dimensions of objects. Friction wear is a slow process of material loss through which, over time, the polymer coating material is worn down equally until the critical diameter, defined as 62mm, is reached.

Take in Figure 6: Photo-eye system for roller inspection.

A pilot system was set up to measure shock vibration of the carts, average grey-scale values, and breakage of the tray inlays and guide roller dimensions.

3. *Research Design Validation*

The pilot test produced data from the 18 January 2019 to the 20 March 2019, measuring the condition of 388,805 passing trays. For every tray, vibration data were captured while passing the conveyor transition. The vibration ranged from less than 1mm/s to up to 20mm/s, depending on the load and metal-base condition. Vibration data were captured while trays were in transition, and data were processed in the condition-monitoring module. The software routinely calculated the peak-to-peak velocity for the vibration.

During the pilot test, it was observed that loaded trays generated peak-to-peak vibration of around 7mm/s and empty trays around 4mm/s peak-to-peak velocity. The average peak-to-peak vibration is about 4mm/s. One of the trays recorded a value 300% higher than the average and, thus, was investigated in further detail. The tray was found to have a distorted rear plate, which was subsequently replaced. Following the repair, the peak-to-peak vibration was measured to be within the average of 4mm/s. This finding confirmed the hypothesis that there is a relationship between vibration generated and the condition of the metal tray base.

Figure 7 is a diagram of the 12 trays that transmitted the highest vibration to the environment.

Take in Figure 7: Trays numbers over vibration.

The second application, which was established using the top camera, was the grey shade average calculation. The mean average grey-scale was used as an indicator of the level of inlay pollution. With the first approach, the image of the inlay was used to calculate the grey shade image. The initial results were not satisfactory; however, as the areas of black cut-outs (inlay edge damage) impacted the result. With the second approach, the image was reduced to an area of 500mm square in the centre of the inlay, eliminating the variations caused by the broken-out sections on the outer edges of the inlay. This approach produced consistent results, with a normal bell curve between 130 and 160, and was a proof of concept.

Results at the image-conditioning station revealed that the range of grey shade values expected was between 80, for a very polluted tray inlay, and 176 for a new inlay. In theory, higher pollution, with darker or black spots, leads to decreasing grey shade average values and a worse case of 0 if the tray is black. As a baseline, the grey shade average values for a brand-new, unused tray inlay and those for a heavily polluted tray inlay were determined by laboratory analysis.

Tray-inlay damage was measured using pixel edge counting. The first results obtained were inconsistent and, hence, unsatisfactory. As the background of the inlay on the image being too light and not contrasting with the tray. The solution was to install two black metal sheets on either side of the conveyor, which created a contrast that allowed the camera to record a clear digital image of material lost on the inlay. Following these modifications led to reproducible values that achieved a tolerance of under 1cm between measurements for the same inlays. In the three months of data collection, the tray with the worst-condition inlay had a section with a total of 142cm of lost material around the tray circumference. Analysing the data available allowed the threshold for the end-of-life parameter for a tray to be set at 100cm.

With the tray metal base facing the camera, images of the two guide rollers were taken. The front roller was checked for wear and the presence of the divert pin. The rear guide roller was only checked for wear.

In a three-day observation period, 37,500 rollers were measured. The majority of rollers were within their useful life, with a calculated diameter range between 68mm and 62.5mm. The sudden fall in data count at 62mm diameter and below is explained by the functionality of the two photo-eye systems that remove trays below this diameter.

Of interest are the impact-damage rollers remaining within the system. The detection by the two photocell methods is highly random because the damaged section would need to be precisely in line with the photocell to be recorded. With the photocell solution, the circumference of the roller and the remaining diameter are calculated using the equation for a circle $d=2*\sqrt{a/\pi}$, which is valid if the roller is round or circular. For damaged rollers, however, the calculated results have inherent errors because the roller is not entirely round in shape.

As stated previously, trays with damaged rollers have a very high risk of derailment when in use and must be removed from service as soon as possible and repaired. So, another test function was added during the pilot test observation phase to achieve this.

This new test focused on roller circumference and compared the most-recent value circumference calculations with the previously calculated values for the same roller. This way, a sudden change in roller circumference could be identified quickly, and remedial action is taken. If the calculated delta in circumference deviated by more than 10%, the likelihood is that the loss of circumference was caused by sudden impact damage. In this condition, trays are removed from service for investigation, even if the roller diameter threshold of 62mm is not reached.

4. *Research Execution*

Once the pilot condition-monitoring station was fully operational, a second test station was installed and commissioned. While the data for a given tray at each station were consistent, the same tray data varied between stations (even with all the same hardware, software, and parameter settings). There could be several reasons for these deviations, for example, different light conditions, however, the variance was calculated as being +/-5%, which was an acceptable tolerance given that the rationale was to identify those trays in the worst condition.

To test whether PdM condition-based monitoring could be applied in practice, the project was split into two phases: proof of concept and diffusion of technology. The second phase involved installing additional monitoring stations in other sections of the BHS. This started once the system was stable. An important factor here was the compression of data, as only a minor deviation in measurements was found between measurement stations. As a result, the amount of data was not directly proportional to the number of stations. The mathematical average provided sufficiently good-quality data for the condition-monitoring solution to be applied effectively across the whole BHS.

The sprawling nature of a major airport BHS, combined with a large number of sensors and monitoring locations, required data pre-processing of data using Edge computing (Mach and Becvar, 2017) and a cloud solution. With all the data uploaded to the cloud and using the IoT features, the development team, with feedback from the field staff involved, was able to create a real-time dashboard with functions that were previously impossible to be realised (Figure 8). The dashboard provided a prior warning that a particular failure or condition was developing (Tickoo *et al*., 2010; Tao *et al*., 2018; Frank *et al*., 2019), which led to the rapid identification of problems (Beaty, 2018), allowing maintenance engineers to react promptly and efficiently to achieve previously challenging KPIs. The condition of 10,000+ carts is recorded and stored in a database, with the history of how the condition develops. Using this data service performance reports, parts consumed history, and operational KPIs can all be presented (Figure 8). Also, two lists are generated, one that can be used as work instructions, the other as work performed.

Take in Figure 8: Tray condition dashboard.

The technical data at the 'Edge device' level is converted into 'operator usable' information at the cloud level, and the system-generated reports allow service operators to prioritise trays needing maintenance based on the actual tray condition. Additionally, the system records precisely which maintenance tasks were performed on which tray and when allowing the collection of information for future trend analysis on the effectiveness of maintenance protocols and spare-part durability by the supplier.

Inspired by the use of image processing technologies in other industries (Sturgill and Detrick, 1986; Lahajnar *et al*., 2002; Ranky, 2003; Patel *et al*., 2012), this approach, together with vibration monitoring, helped to prevent unexpected system downtime and allowed maintenance staff to focus their efforts on other important activities (Rao, 1996; Carden and Fanning, 2004).

A major success of the project was the complete elimination of tray derailment. Before the study, derailments happened weekly, but since the change, not a single derailment event was reported in more than five months, and this is agreed as a significant success

Discussion of Results

Before the implementation of the CBM solution, the status of the tray fleet was unknown. The round-robin principle used in organising human inspection and maintenance was unreliable and resulted in a high incidence of derailed trays caused by under-diameter guide rollers. With the development of an automated CBM system, it was found that advanced sensor and image processing technology could cost-effectively be used to convert an airport BHS maintenance strategy from a preventive, ‘time-based’ strategy to a predictive ‘condition-based’ strategy (Mobley, 2002; Hashemian and Bean, 2011). Our results from the pilot study are aligned with existing literature regarding the use of advanced technologies and I4.0 solutions to improve the cumulative capabilities simultaneously (Ferdows and De Meyer, 1990), resulting in improvement in quality, speed, dependability, flexibility and cost metrics linked to operations and maintenance processes.

This study demonstrates the efficacy of CBM systems (Tickoo *et al*., 2010; Hashemian and Bean, 2011), although further long-term studies are required to evaluate the full potential benefits of the tray-fleet monitoring system. Including, but not limited to, the identification of system design flaws, the identification of bottlenecks and damage locations, the need for / elimination of redundancy equipment, supplier spare-part quality assessment, and the effectiveness of maintenance interventions.

The size and complexity of airport BHS will no longer be a constraint for condition-based monitoring and spare-part quality and asset design improvements will result from data-trend and root-cause analysis. This change is likely to significantly impact how future proactive maintenance operations are carried out in major city and other airports. Resulting in improved reliability of airport assets, improved productivity and cost savings with enhanced customer satisfaction and service.

Also, rather than investing in new hardware, this solution utilised existing assets that were equipped with low-cost sensors and industrial gey-scale cameras to capture real-time data. The data was processed using advanced technology to provide information that could be used effectively to predict when maintenance is needed. This solution avoids substantial capital investment and can also be employed in a live system very quickly.

Conclusions

According to Fraser *et al*., (2015), there are several thousand articles on conceptual and mathematical modelling of maintenance management, but there is a distinct lack of empirical evidence of real industry problems. Of the empirical papers identified by Fraser *et al.,* (2015), there were only 26 on CBM and none of these from a logistics service perspective. This paper seeks to address that and contribute to knowledge that can be applied to academia and practice.

The Theory of Performance Frontiers (Schmenner and Swink, 1998) has primarily focussed on the operational frontier and is linked to the Theory of Swift Even Flow (Schmenner and Swink, 1998; Holweg *et al*. 2018) where the operational frontier is considered to be bounded by the asset frontier. These studies are often related to operational improvements through implementing Lean (Samuel *et al.,* 2014) and Process Theory (Holweg *et al*., 2018) where there is considered to be a trade-off between capital investment and is subject to the law of diminishing returns. Although we are not challenging the basic premise of the asset frontier in a manufacturing environment, as this has not been tested, we are contributing to this debate by providing empirical evidence to support the implementation of CBM to improve assets in a logistics environment that includes the interconnection of multiple moving assets. In the context of an airport BHS the overall performance of a system can be enhanced without costly capital investment by simply taking a systems architecture approach and combining new technology, advanced data processing, and existing assets and low-end hardware.

Industry 4.0 and the IoT continues to move the asset frontiers out by extending the useful life of assets and providing data for the enhancement of maintenance practices (Tao *et al*., 2018; Frank *et al.*, 2019). The effective use of technologies of I4.0 (Frank *et al.*, 2019) such as Edge and Cloud computing, IoT, Big Data, and data analytics means that operations and maintenance processes can now gather data in real-time. Data gathered from sensors and processed in real-time using advanced data analytics provides useful information to a maintenance team to conduct 'Smart Maintenance' to avoid unexpected downtime or failure (Tao *et al*., 2018).

Future Research Directions

The focus of this research was a single airport BHS and, more specifically, technical solutions for the condition monitoring of DCVs in the systemThe use of similar logistics systems extends across multiple airports and industries (e.g. the courier industry), all of which could benefit from the application of the Industry 4.0 and IoT solutions explored in this study. The ease and low cost of implementation in brownfield sites apply to all running operations, and the ability to source real-time condition-based data from multiple assets and locations facilitates any CBM strategy, irrespective of industry.

Future studies may also benefit from learning the key similarities and differences between TAR and design science approaches to provide guidelines for researchers on how to use them more effectively in architectural innovation to move the asset frontier forward to enable further operational improvements to deliver higher levels of system performance.

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Figure Headings

Figure 1: Performance Frontiers (adapted from Schmenner and Swink, 1998)

Figure 2: Technical action research process, (adapted from Wieringa, 2014)

Figure 3: The Engineering Cycle (adapted from Wieringa, 2014)

Figure 4: Pilot test with Edge and cloud computing technology

Figure 5: Relationship between vibration generated and metallic frame condition

Figure 6: Photo-eye system for roller inspection

Figure 7: Trays numbers over vibration

Figure 8: Tray condition dashboard (Source: Siemens, reproduced with permission)