Measuring and Improving the Productivity of Construction's Site Equipment Fleet: An integrated IoT and BIM System

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Abstract

Annual productivity growth within Construction has increased by just 1% in over 20 years (McKinsey, 2017). A key contributor to this performance issue is associated with the management of construction's equipment fleet. Site equipment represent a significant percentage of the total cost of projects; are a critical 'bottleneck' resource that is linked to delays, and a major contributor to on- and off- site congestion and air pollution. Their effective management represent a key opportunity for economic, environmental and safety efficiency gains.

Research and development efforts aiming to address this challenge are on the rise in both industry and academia. Much of existing studies try to exploit opportunities made available by the Internet of Things (IoT). Studies are addressing accidents prevention, measurement of operational efficiency, monitoring equipment health, and improving equipment deployment. Equipment default telematics systems are increasingly providing important operational data (e.g., working hours, fuel consumption, fault code, etc.) but these have many limitations such as: they are restricted to heavy equipment; they do not capture all data required for effective management of construction equipment fleet, and data is not aggregated from across disparate systems to enable intelligent decisions. Moreover, data from IoT systems is not linked to any Building Information Modelling (BIM) environment (e.g. 4D BIM), making it challenging to contextualise the operation of construction fleet equipment and to inform more intelligent and proactive deployment decisions.

This paper proposes an integrated IoT-BIM system for the management of site equipment. Eight interviews were held with experts from the largest infrastructure projects in the UK to identify the key challenges facing site equipment fleet and the key use cases to be addressed. A review of existing telematics systems was performed to identify their capabilities and limitations in relation to an integrated IoT-BIM solution for the identified use cases. An early architecture of the proposed IoT-BIM system is described. The proposed system requires i) the collection of data from disparate telematics systems and the development of tailored IoT devices for data generation and collection, ii) machine learning algorithms to interpret the data for the use cases' decisions, and iii) data and information from both the IoT and the machine learning unit into the 4D BIM environment and the dashboard visualising the performance for the selected use cases.

This work is part of a joint industry-academic effort co-financed by Innovate UK as a feasibility study project under their 'Increase Productivity, Performance and Quality in UK Construction' competition.

Keywords: BIM, IoT, Machine Learning, Productivity, Use Case.

1. Introduction

Advances in digitalisation are enabling new ways for investigating rooted challenges with the construction sector. Together BIM, which is the current expression of digital innovation within the construction sector (Succar and Kassem, 2015), and the Internet of Things (IoT) are transforming the way built assets are designed, constructed and operated. One such a challenge at the construction phase is the effective management of site equipment fleet. Exploiting digital advances for this challenge is motivated by the significant incidence of construction equipment on the cost and schedule of projects and the opportunity of increasing their productivity (e.g. utilisation rate, reliability/availability, etc.) and reducing their environmental, health and safety impact. The prevailing current practices in management of construction equipment management are highly dependent on individuals' experiences. Data on construction equipment operations is recorded by contractors sporadically, if at all. The data is stored in different cost centres such as a project site or a fleet, forming siloes or 'information islands' that are hardly communicated, or known, to other decision-makers. Finally, comprehensive data sets that can cover the entirety of construction equipment fleet on site is still lacking despite being highly demanded by fleet project managers and executives (Niu et al., 2017).

This paper proposes an integrated IoT-BIM system for effective management of construction site equipment fleet. Section 2 summarises some of the key studies addressing site equipment productivity through digital advances. Section 3 reveals the findings from 10 interviews with experts from major infrastructure projects in the UK about current practices, key challenges, and top use cases. Section 3 briefly describes the proposed framework. Section 4 discusses and concludes the paper.

2. Literature review

The upsurge in research investigating new ways and systems for improving site equipment fleet management is motivated by the advancement and affordability of IoT sensing devices and increased adoption of BIM. Studies available in the literature are addressing various aspects related to the management of site equipment including: equipment usage patterns, fuel consumption and carbon emission, safety and access to equipment, routine and preventive maintenance, servicing strategies (i.e. repair or replacement), procurement strategies (i.e. buy or lease), fleet allocation/deployment, and fleet tracking and localisation (Niu et al, 2017). This section provides a summary of the key studies in this realm.

Fang et al. (2016) developed a system by combining BIM and cloud enabled Radio Frequency Identification (RFID) localization systems to enable the localisation of indoor mobile construction resources. The testing on site and discussions with site engineers and managers indicated that the proposed RFID indoor localization system has a great potential in practical applications such as site security control, safety management, and first responder rescue. Zhou and Ding (2017), through combining RFID, tracking technology, ultrasonic detection technology, and infrared access technology into a three-tier network architecture, developed a system that assisted site workers in changing their risky behaviours and accident avoidance in underground construction sites. Zhifeng et al. (2016) developed a similar system for mobile cranes that facilitated remote monitoring and accident analysis. Kanan et al. (2018) developed, by combining sensing systems based on three techniques (i.e. radio frequency, directional antennas, and ultrasound waves), an IoT-based autonomous system for monitoring the safety of workers on site. This sensing system was installed on the rear of site equipment and used in conjunction with a workers' wearable device that includes a radio transceiver (transmitter/receiver), a wake-up sensor, an alarm actuator, and a General Packet Radio Service (GPRS) module. The combination of the two systems helps in monitoring, localising, and warning site labourers of proximity dangers.

Lu et al. (2011) explored the application of Radio Frequency Identification (RFID) technology in assisting the management of material, men and machinery on site. In relation to machinery on site, potential applications that were identified include tracking of machines and tools, machine operation permission systems and utilisation records, and machine maintenance records.

Zhong et al. (2014) proposed an IoT system called 'Safety Management System for Tower Crane Groups'. The system is used to detect the operating status of each tower by a set of customized sensors, including horizontal and vertical position sensors for the trolley, angle sensors for the jib and load, tilt and wind speed sensors for the tower body. The sensor data is collected and processed by the Tower Crane Safety Terminal Equipment (TC-STE) installed in the driver's operating room. Wireless communication between each TC-STE and the Local Monitoring Terminal (LMT) at the ground worksite were fulfilled through a Zigbee wireless network. LMT can share the status information of the whole group with each TC-STE, while the LMT records the real-time data and reports it to the Remote Supervision Platform (RSP) through GPRS. Based on the global status data of the whole group, an anti-collision algorithm was executed in each TC-STE to ensure the safety of each tower crane during construction. Remote supervision was fulfilled using the client software installed on a personal computer (PC) or smartphone. Niu et al (2017) proposed a system that enabled the collection of site equipment's operational data and the production of analytics for their management. The two key components of the proposed systems were: (1) a smart chip that integrates various sensing and communication modules for proactively collecting and exchanging from daily equipment operations; and (2) a data analytics platform for data storage, visualization and analytics. The approach used by the authors consisted of using the concept of "Smart Connected Objects (SCO)" where construction resources (e.g., machinery, tools, devices, materials, and even temporary or permanent structures) are made smart by augmenting them with sensing, processing, and communication abilities. With this they have autonomy and awareness, and can interact with the vicinity to enable better decision making. Ahn et al. (2013) developed a system for the operational efficiency and environmental performance of site equipment. Controlling the operational efficiency of equipment is key to managing and improving the environmental performance of construction operations. Their method was based on using vibration signal analysis to monitor the operational status of equipment.

Aslan et al. (2012) developed a system for enhancing the operational productivity of site equipment by combining GPS, WSN, and web applications. Their focus was to provide information on raw data integration and productivity data analysis for the development of fleet management metrics to identify areas of improvement (e.g. guideline to managers, effective equipment operations, resilience and flexibility improvement, and cost reduction).

Said et al. (2015) developed a telematics-based equipment health-monitoring framework to support fleet service managers in using telematics data in their predictive maintenance programs. The framework consisted of two modules: (1) the health parameters processing and visualization (HPPV) module; and (2) an equipment failure hazard estimation (EFHE) module. A recent review of studies in this area is also available in Zankoul et al. (2018).

Object recognition techniques are currently used for tracking construction processes against BIM data. Wu et al. (2009) use object recognition to compare construction-site photographic images against 3D BIM models to assess construction processes. This approach extracts objects of interest such as concrete columns from site images and uses advanced imaging algorithms to compare 3D objects from the BIM design model to detect objects within the site images.

Gledson and Greenwood (2016) state that the key advantage of 4D BIM is the handling and communicating of information to improve understanding of planned activities. Hakkarainen, M. et al (2009) discuss the use of 4D modelling and augmented reality to check planned vs actual on site. Sulankivi, K. et al (2013) discuss the automatic recognition of health and safety issues in 4D modelling during the design process. But there is currently lack of studies looking at linking live data to models to show what is happening live on a site, and this paper is starting to explore this potential.

Some of the key limitations of existing studies include: limited input from the industry in relation to the required use cases; use of a limited set and types of data; limited use of machine learning to transform/optimise decisions; lack of integration with BIM environment to contextualise the deployment of equipment and inform the planning/deployment process of equipment; and limited development in dashboards to visualise equipment performance from across the entire equipment fleet.

3. Review of telematics systems

Telematics refers to any integrated use of wireless communications, vehicle monitoring systems, and location devices to provide real-time spatial and performance data of fleet machines (Aslan et al., 2012; Said et al. 2015). Application of telematics in construction site equipment is a way not only to assess existing equipment productivity but also to provide a baseline for future productivity improvement, optimising operation planning, and establishing long-term strategic organisational objectives (Aslan et al., 2012). A usability review of telematics systems for construction equipment fleet management is included in Jagushte (2017). The commonly collected parameters by such systems include: actual machine operating hours, machine location, machine health, and fuel consumption. The review revealed challenges that affect the use of these systems; such as the difficulty in storing the data collected and performing the required analytics (e.g. interpretation of high volume of data), and acceptance of the technology by professionals who deem to be implementing good equipment fleet management practice. Some standards and third party telematics systems providers are emerging to develop a more universal solution to the data collection from across the wide and varied equipment included in a site fleet. Some international standards such as the ISO 15143-3 (previously known as the AEM/AEMP Telematics Standard) are also emerging to address the challenges of collecting data from mixed fleet Telematics systems.

The authors have performed their own review of commercially available telematics by Original Equipment Manufacturers (OEM). The systems were anonymised (i.e. Supplier 1, 2, etc.) for confidentially and commercial purposes. The results of the review are summarised in Table 1.

The performance areas measured are included in the heading of Table 1. The review found that there is often inconsistency in the reporting of such performance areas. For example, 'fuel used' and 'engine on hours' are reported cumulatively in some systems but are reported daily in other systems. 'Location' is provided at a variable point in time during the day across the different systems. Distance is reported as the cumulative distance travelled in some systems while distance travelled during a timeframe by other systems. Load factor which is the capacity at which the equipment was working compared to its maximum rating (such as maximum weight carried) or output function, an important key performance indicator for measuring productivity is not measured by existing telematics systems. In the vein is the 'working' function which measures the amount of time the asset spent in each working state, idle, travelling or working. Fault data are captured in one system only. Most of the measured data is not available in real time or near real-time and most system, with the exception of few, have reliability issues, characterised by issues related to transmission of data and accuracy of transmitted data.

Table 1 Review of telematics systems

OEP	**Data Reliability**	**Fuel Used**	**Fuel Remaining**	**Engine on hours**	**Idle Hours**	**Location**	**Distance**	**Load Factor**	**Working**	**Fault Data**
Supplier 1	97%	Y	Y	Y	Y	Y	N	N	N	N
Supplier 2	95%	N	N	Y	N	Y	N	N	N	N
Supplier 3	99%	Y	Y	Y	Y	Y	Y	N	N	Y
Supplier 4	41%	Y	N	Y	N	Y	Y	N	N	N
Supplier 5	56%	Y	N	Y	Y	Y	N	N	N	N
Supplier 6	77%	Y	N	Y	N	Y	N	N	N	N
Supplier 7	29%	Y	Y	Y	Y	Y	N	N	N	N
Supplier 8	82%	Y	Y	Y	N	Y	N	N	N	N
Supplier 9	<5%	N	N	N	N	Y	N	N	N	N

4. Interviews with experts

As identified in Section 3, there are a range of telematics systems available with which to measure and monitor construction site plant and equipment (PE) operation and performance. However, questioning what data should be collected and for what purpose (i.e. defining use cases) has been fundamental to designing an appropriate study for application of IoT devices and data services. The current research therefore carried out interviews with a range of stakeholders to reveal the most viable or beneficial use cases to which IoT devices and data analysis should be applied.

The questioning framework focused on issues that are known to impact time and costs within construction projects, including: planning and scheduling of PE (budgeting, specification), management of PE onsite (logistics to and from site, movement onsite, fuel/refuelling issues), hiring and supply chain processes, management of statutory requirements (e.g. carbon reduction), utilisation of PE, and management of failure and maintenance.

The selected interviewees either directly interact with PE (including specification, scheduling, and operation) or where the role did not directly interact with PE was impacted by the performance and cost of PE. The roles included project director, project manager, plant & equipment manager, organisational development professionals (lean practitioners), site foreman, surveying and monitoring staff, health and safety professionals and compliance managers.

All interviewees worked for the Costain Skanska Joint Venture (CSJV) at the High Speed Rail 2nd Phase (HS2). This particular programme of work involved excavation and enabling works, demolition and ground remediation. Key challenges cited by the interviewees included: operation of PE within confined and covered work areas, archaeological sensitivities (the site is a burial ground which required exhumation of over 10,000 bodies), is a Central London location, and where the client (UK Government) has mandated over 400 undertakings and assurances (UAs) which require self-management and reporting by CSJV.

A summary of the use cases elicited is presented in Table 2. The summary represents a consensus of use cases and identification of any associated metrics that are recorded/reported during the contract by the CSJV. This data is to be used as the basis for determining how and where the IoT hardware will be deployed, i.e. which plant or equipment, work actions to be monitored, and measures/features to be recorded within the capabilities of the sensing devices; namely vehicle engine activity, video surveillance of moving parts, and acoustic anomaly monitoring (i.e. fault detection.) A detailed account of the IoT hardware used for this project is presented in Section 5.

Use cases 1, 2 and 3 (Table 2) have been chosen for application of IoT devices and data streaming/analysis.

Use case 1: Total volume of material excavated: A key metric cited by the interviewees is the volume of spoil being excavated and removed from site. This is an output based measure against which the project was originally budgeted and was evaluated daily during the project. Complications identified the inability to make use of pre-existing telemetry fitted to PE due to inconsistencies and incompatibilities of systems. For example, lorry pay load scales were found to be unreliable. Supplementary measuring devices were therefore employed including laser scanning by drones to measure topology changes from which volume removed was estimated. Furthermore, the granularity of data measurement meant that productivity and utilisation of individual PE was not possible. Manual measurements are reported daily for each work zone. The current research aims to provide live streaming of productivity rates for individual PE assets. It was reported that a major challenge in effective estimation (budgeting and costing) prior to commencement of the work was how to quantify the productivity of archaeologists supported by mechanical dig equipment. This has never been accurately quantified prior to this project. The site being a burial ground also required sensitive excavation with often labour intensive elements to ensure respectful removal of bodies. A target of 1.25 metres cubed per archaeologist per day was set. Management of labour numbers and PE utilisation is therefore difficult to measure and monitor. The current research will therefore aim to improve the granularity and quantification for mixed labour-mechanised utilisation rates.

Table 2 Key plant and equipment measures and use cases

	Use case	Measure	Count
1	Productivity (archaeologist excavation rates per labour unit (1.25m^3 /day/head)); PE utilisation rate	Total material volume (m^3) removed	3
2	Audit (Control Board reports); PE specification versus utilisation rate	Cost/budget tracking	3
3	Progress reporting (Control Board); lean management (behavioural change analysis); scheduling	Job/task completion rate (% measure assigned) (planned versus actuals)	3
4	Traffic management planning (offsite logistics)	PE location	3
5	Monitoring and reporting undertakings and assurances; breach notifications; PE and operator fitness for purpose onsite; self-management capability assurances	Consents/compliance measure (e.g. emissions, noise)	3
6	Health and safety	Risk hours saved	1
7	Sustainability of construction, environmental compliance	Fuel/battery efficiency	1

* Count represents the number of interviewees making reference to the identified use case.

Use case 2: Control board monitoring. Audit of PE use is carried out at daily and weekly intervals by drawing data from disparate sources. The Control Board use a business intelligence (BI) software package to keep track of utilisation of PE and cost management. Data is imported to the BI from an array of sources including spreadsheets, manual reports and available telemetry and aggregated to project level which is a cumbersome and time-consuming approach. The current research intends to look at how asset specific utilisation measurements can be formed in to a continuous and synchronous dataflow, where data is live streamed and aggregated to provide meaningful project measures. This will provide a high level of connectivity between individual assets and overall project outcomes to improve PE specification, deployment and utilisation.

Use case 3: Project tracking. The final use case to be applied using IoT will be 'Progress Reporting'. A condition of the contract is for the CSJV to communicate progress with the client on a regular basis. Such evaluation of planned works versus actuals forms a significant value proposition for the relationship between IoT and 4D BIM modelling. The current research aims to assess the feasibility of providing snap-shot analysis of project progress and live PE tracking. Such visual inspection capabilities would afford decision-makers a powerful tool with which to identify bottle-necks, conflicts and clashes on projects which would be a major break-through in achieving efficiencies and stakeholder engagement.

The remaining use cases; traffic management planning, UAs monitoring, health and safety and business improvement (sustainability) have not been taken forward for research at this time. These use cases were determined to require more complex data measurements than could be supported by the IoT devices available.

5. Proposed approach

The proposed approach (Figure 1) is described in four parts: IoT hardware; asset inventory and business intelligence dashboard; machine learning; and 4D BIM.

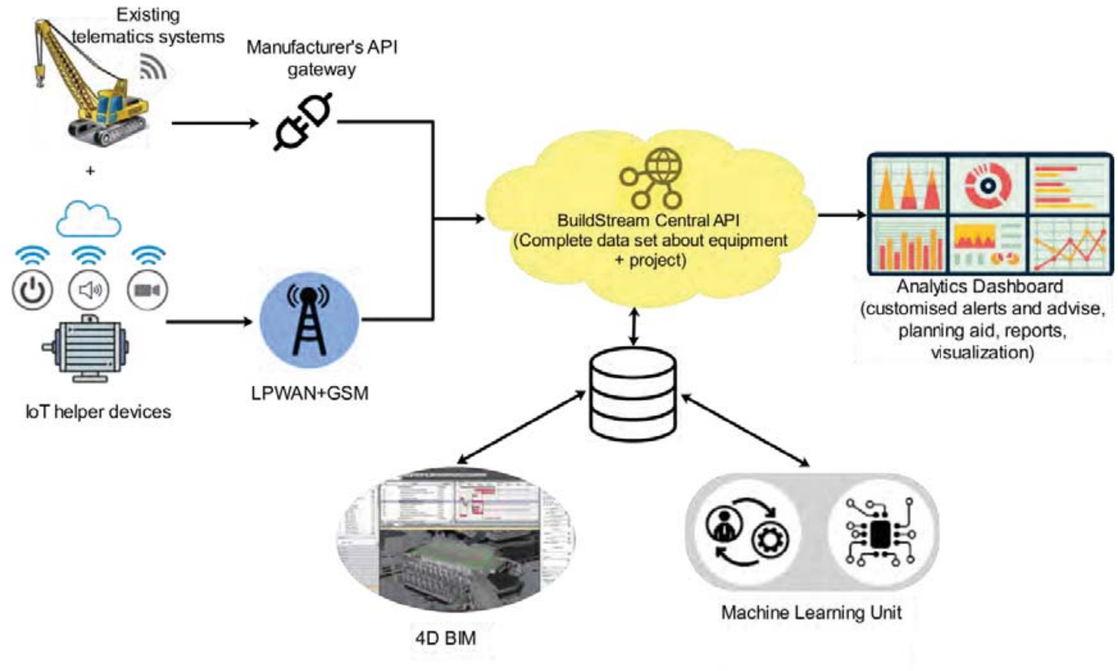

Figure 1. A simplified architecture for the system

The IoT device: includes a data logger, a camera, a microphone and a modem which allows the device to communicate data via GSM networks. The information is sent to the cloud-based database and can be used by the various modules (4DBIM, MLU) and the results are visualised on the web app.

The asset inventory and business intelligence dashboard (Figure 2): collates all existing data from telematics systems already installed on the equipment assets through API connections, providing one consolidated location for this information, which is then put into the context of the specific project. The data is stored on AWS servers and the web app / dashboard pulls the data from AWS into the front-end application. Individual assets, or groups of assets can be analysed by the project teams to determine areas of interest where operational interventions can be made to increase the efficiency of site operations.

The machine learning unit: The feasibility of identifying (either predicting a future state or inferring a current state) of PE using machine learning is being explored in this project. With reference to the use cases identified in Section 4, data sets are being evaluated that would support the prediction or inference of productivity and utilisation of PE; where productivity might be a measure of 'volume of soil excavated/unit/hour' and utilisation is a measure of the actual 'working state /unit/hour'.

The IoT hardware: measures three data items: location (via GPS), audio (via microphone), and vision (via camera). It therefore has three data sets which can be used to predict/infer productivity and utilisation. For the purpose of this paper, only the video stream data is being used to train a supervised learning ML algorithm by segmenting existing video footage of three classes of digger activities (Figure 3). Video segments are labelled with the activity (or class) that is being observed within the segment. A multi-class classification is being sought with three classes: 'working – digging', 'working – no digging', 'idling', where the algorithm is predicting one class from the three discrete classes.

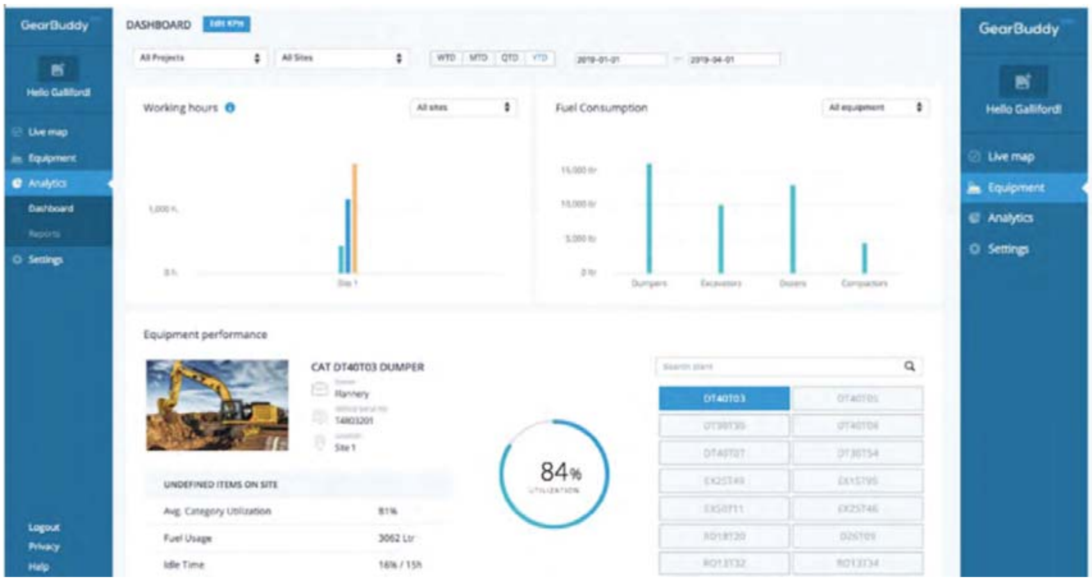

Figure 2. Collation and visualisation of data from site equipment fleet

Key challenges that the current project faces is the volume of data, i.e. the number of video segments required to deal with the complexity of the problem of class inference. The classes are similar to each other in appearance. For example, the motion of a 'digging arm in soil' is subtly different from a 'digging arm simply moving to position'. Based on classical rules for ML vision algorithms, the project is seeking more than1000 video examples per class. This must also include a diverse range within the problem space for each class (e.g. 'working – digging'), this might include: different operating environments, i.e. different ground colours, different light levels, wet/dry ground; different manufacturer arm types, or different camera angles, video resolution and frames per second. Once the classes have been detected, the system make this data available which can then be converted in productivity measurement and PE utilisation rates as described in the Use Cases table. This approach represents an improvement compared to the existing telematics solutions where (1) such granular measurement is not possible; and (2) data is not available in one consolidated platform. Moreover, data models from the IoT devices and 4D BIM model will be created and tested against the trained model to make best fit predictions on the likelihood of changes to the construction project process. The project will not, at this stage, be looking at deploying this full ML solution, i.e. that is to build a data pipelines that extracts data from the IoT devices, transforms, predicts and imports to 4D BIM. This will be an offline activity in order to evaluate the accuracy of the proposed end to end solution in meeting the objectives of the use cases.

4D BIM: To provide context for the deployment and productivity of PE within the planning process and enable proactive decisions about their deployment, links with 4D BIM plans for site management are proposed utilising a commercially available 4D BIM software. Links will be explored using both live data and offline data from the IoT sensors. Live data into the 4D BIM model will be used to link and visualise which equipment is active on specific tasks within the project (e.g. how many and which excavators are working on digging a hole activity, and how many and which access platforms are working on installing cladding activity). This will support in the reporting of progress, the utilisation of PE on site and the use of visual method statements. A plant and equipment library will be also built to provide a realistic representation of the equipment within the 4D schedule. Use of this 4D BIM linked environment over time will provide sufficient offline data for further intelligent decisions in future. For example, the trained model can be used to make predictions on the likelihood of changes to the construction project process associated with PE. This capability will require the further ML functionalities to learn about the relationship between PE utilisation and project progress from images generated by the augmented 4D BIM system.

6. Discussions and Conclusions

Construction equipment is a critical resource in most construction projects. Current inefficiencies in management of site equipment fleet, recognised in both research and practice, is a key contributor to the gap in productivity performance of construction projects and the whole sector. Advances in digitalisation enabled by BIM and IoT, accompanied by increased affordability of sensing devices, are opening new ways to investigate this challenge. In response to this challenge and the key shortcomings of both existing studies and commercially available telematics systems, this paper proposed an integrated BIM-IoT system for Measuring and Improving the Productivity of Construction's Equipment Fleet. Limitations in existing studies included limited engagement with the industry in relation to the use cases addressed (e.g. identification and prioritisation of use cases); use of a limited set and types of data; limited deployment of machine learning to transform/optimise decisions; lack of integration with BIM environment; and limited development in dashboards to visualise equipment performance from across the entire equipment fleet. Commercially existing telematics systems have an inconsistent approach to data capture and reporting; capture a limited number of data items that are not sufficient to measure the productivity of either an individual equipment or an entire fleet; and are affected by reliability issues related to transmission of data and accuracy of transmitted data. The proposed system integrate data from an entire fleet in a near real-time manner and enables the measurement of equipment productivity. The proposed system was tailored for three of the uses cases that were most frequently mentioned by the 10 experts interviewed. The system consisted of IoT hardware; asset inventory and business intelligence dashboard; machine learning; and 4D BIM. Each of this component and the architecture of the whole system was described. The current progress in the development of the tool include the IoT device, the dashboard and the machine learning unit. A brief demonstration of the prototype was provided. It showed how the system uses the video stream data to predict three classes, 'working – digging', 'working – no digging', and'idling', of equipment status using a supervised learning ML algorithm. The dashboard collating data from across an entire fleet was also demonstrated. Future development will include (1) assessment of the accuracy of the productivity measurement achieved by benchmarking predicted against actual. This work is required to complete Use Case 1 and will necessitate the collection of a significant video footage to address the challenges facing the implementation of the ML algorithm; (2) addressing Use Cases 2 and 3 and completing the implementation of links with the 4D BIM environment; and (3) holistic testing of the whole system on an entire site equipment fleet.

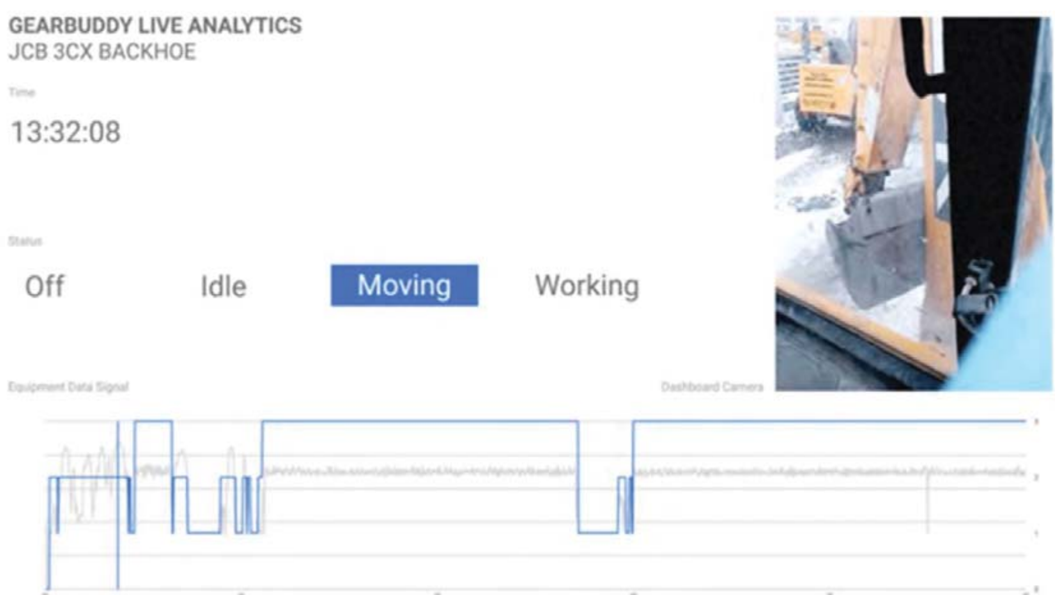

Figure 4. Supervised learning ML algorithm predicting three classes of digger activities.

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