Portable and Non-Intrusive IoT-Enabled Monitoring of Activity and Emissions: A Use Case in Diesel Container-Handling Equipment at Ports

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***Abstract*—Container ports provide a critical supply chain component between marine and land transport systems. The transported cargos are carried within uniformly sized shipping containers and landside handled by standardized handling equipment. This equipment moves and positions containers within storage yards, with deposition onto trailers for haulage onto ships wharfs and hinterland deliveries. These handling activities often require large numbers of mobile equipment consuming significant quantities of diesel fuel for powering internal combustion engines with exhaust carbon emissions. Quantifying these carbon emissions is typically estimated by applying average emissions factors onto the diesel usage records without measurement verification. This paper discusses an IoT based portable and non-intrusive sensor system for monitoring ports container handling equipment activities and exhaust emissions. The sensor system was developed and tested on Reach Stackers and Yard Tractor-Trailers in a container port. The study approach ensured the applicability and versatility of the sensor system for use on a range of equipment types. A key attribute for collecting data was the use of action cameras to capture screen numeric information for translation into digital data. This was combined with an engine exhaust gas analyzer, together with (when available) engine management data from the Engine Control Unit, and dashcam recordings of the vehicle activities. The port trials results proved the deployability of the sensor system with sample duty-time profiles that characterized the container handling equipment activities on a seconds time basis. These duty-time profiles provide baseline data for predicting diesel usage and exhaust emissions from the monitored parameters. The trial results can assist in identifying the potential for reducing fuel usage and emissions to decarbonize ports container handling equipment.**

***Index Terms*—IoT, Sensors, Ports, Container Handling Equipment, Emissions and Activities Monitoring**

I. Introduction

Portable Emissions Measurement Systems (PEMS) and Portable Activity Monitoring Systems (PAMS) are used to monitor a vehicle's emissions, track its activities, with profiling of the machinery operations and parameters. These systems combine exhaust gas analyzers, engine intake or exhaust gas flow metering, Global Positioning System (GPS) locations and movements, with engine management control and diagnostics signals to provide real-world journey data with emissions tests [1].

From the Internet of Things (IoT) perspective, which represents a paradigm of connecting multiple sensors to the internet [2], these systems integrate various sensing units for data collection, monitoring, exchange and analytics to enhance operational improvements. Vehicle attached PEMS capable of providing real-time data can considered IoT devices for sampling engine exhaust emissions, while PAMS are used to record machinery activities and performance. Overviews of PEMS technologies are presented in [3] and PAMS in [4].

Notably most new heavy duty vehicles include PAMS technologies from accessing engine management control and diagnostics signals which are standardised through the worldwide protocol SAE J1939, a guiding introduction is presented in [5]. Examples of the use of PEMS and PAMS specifically intended for port mobile heavy duty equipment are presented by [6], [7] for Yard Tractors and [4], [8] for Drayage Trucks. Vehicle type specific systems can be developed by transferring and applying sensor systems used for cars and light commercial vehicles, an example being [9]. Additionally commercial PAMS products are available to include dashcam imagery combined with vehicle telematics for operational monitoring, an example is presented in [10].

This paper summarizes a study to develop, undertake in-port trials, process results data, devise analytical tools, and deliver example results from using an IoT-enabled PEMS–PAMS-camera monitoring system on ports diesel fueled internal combustion engines for container handling equipment. The aim was to provide extra information and versatility for capturing and characterizing port handling equipment duty-time profiles. This approach is useful for when, vehicle engine control system and status signals are inaccessible, avoids accessing protected signals and confidential data, and can monitor older vehicles with limited instrumentation. These were all practical issues encountered and mitigated by this study's approach.

II. Study Focus

Therefore the study focus was to develop and implement a portable and non-intrusive sensor system which included cameras for monitoring in-port container handling equipment diesel fuel usage, available vehicle operational parameters, exhaust emissions, and duties on the seconds time scale covering idle, laden and unladen periods. The in-port trial results were intended to provide a baseline dataset for characterizing diesel powered container handling equipment duty-time profiles.

III. Sensor System Development for Port Trials

For the delivery of the in-port trials (Section V) the developed sensor system was specified to conform with two key criteria. Firstly it was to minimally intrude on handling equipment and port operations, avoid distractions to the drivers, with fast and safe attachment for minimal vehicle downtime. The second, were that the system needed to be; low cost, portable, flexible, lightweight, used portable rechargeable battery pack or dashboard power, weather protected, reliable with sensors redundancy, be safe, and compliant with airline passenger weight, size, and battery regulations for carriage to and from the port.

The sensor system trials also required the permission from, and cooperation with, a container port. This was provided by the Kuching Port Authority for their Senari Container Port, Sarawak, Malaysia. The port uses a standard terminal layout with ships berthing at its single wharf with quay cranes used for the ships loading and unloading of containers. The containers were hauled by Yard Tractor-Trailers between a storage yard area and the wharf. The containers were then stored in stacks of up to three 20 or 40 ft containers high, and up to five rows deep, with the in-stack positioning undertaken by either Reach Stackers or Rubber Tired Gantry Cranes, [11]. The containers landside haulage also required their loading and unloading with Road Truck-Trailers from outside of the port.

This paper focuses on ground based Reach Stackers and Yard Tractor-Trailers. These equipment types cover a container ports key handling tasks, spanning a wide annual average load factor range (reported at typically 39 to 59% respectively, [12]), resulting in diesel fuel usage with engine exhaust emissions typically ranging from 2 to 23% respectively of a ports total estimated emissions, [13]).

This study's devised sensor system was comprised of, 1) the vehicle Energy Management Signals (EMS) available data which was video recorded by action-cameras, 2) the recording of vehicles activities by front and rear video dashcams, with 3) an Exhaust Gas Analyzer (EGA). Each sensor had a dedicated data logger, time referencing and power supply within a decentralized system. For the Reach Stackers direct access to the EMS signals was unavailable and so the dash-display information was video recorded, whereas for the Yard Tractors the EMS data was accessible through an EMS signals reader and the reader screen information was videoed. The port trials sensor locations attached to the port equipment are shown in Figures 1 and 2.

Notably, extra sensors for measuring ambient weather conditions, engine exhaust or engine air intake flows with gas density were deliberately excluded from the developed sensor system as the intent was to minimize the; airline carriage weight, additional instrument calibration and setup times, and the intrusion on the port vehicles scheduling and current engine performance. Therefore and firstly, an open source online local weather station dataset was identified to provide hourly averaged weather data for the port locality. Then secondly, as the EGA sampled the engine exhaust gases on a percentage by volume basis these are convertible to chemical molar weights mass ratios with conversion into mass flows using the combined engine intake or exhaust gases mass flow rate. The engine exhaust mass flow rate may be estimated based on the vehicle engines known cylinder displacement and scaled by an assumed typical volumetric efficiency and turbocharger mass flow scaling that increases with the recorded engine speed, plus an adjustment for the engine intake gas density. This estimation approach, although less accurate than by using direct parameters measurement, enabled the trials to be practically undertaken in an operational port. The approach highlights this study's compromise made between minimizing the intrusion on the port activities versus the results accuracy. Note also that to manage this paper's content the EGA results are shown on a percentage by volume basis in Section V.

IV. Port Trials Data Collection & Processing

The sensors system was installed on two Reach Stackers and two Yard Tractors in the Senari Container Port in 2024. A total of 16 separate trials, with 8 trials per vehicle type were undertaken. Each vehicles activities were monitored in handling containers to a typical maximum of 38 tonnes using the ports' weighbridge. The trials provided 8.31 hours of data for the Reach Stackers and 7.68 hours for the Yard Tractors, with example results for a Reach Stacker shown in Figure 3. The sensor system typically took 45 minutes to install, and 20 minutes to remove from, a Reach Stacker, or a Yard Tractor, and did not significantly delay operations.

After the vehicles normal port activities had been monitored and recorded from each trial run, the sensors data loggers (see Figures 1 and 2) were downloaded for data processing and quality reviewed prior to analysis. The data processing differed between the EGA and the action cameras. The EGA data was timestamp recorded every 0.5 secs from a reference time and logged onto a Raspberry Pi in Comma-Separated Values (CSV) text file format. This text data was then converted to numeric within a spreadsheet. A time adjustment was then assessed and imposed on the time data to align with the vehicle camera recorded activities due to the EGA gas sampling time lag. The action camera's video data from the EMS reader, cabin dashboard and cabin dash-display screens were stored on SD cards and after downloading required new software tools to extract specific video frames every 0.5 secs. To then translate the video frames number images into numeric digits for spreadsheet analysis required this study to specifically develop a set of Python code algorithms.

The camera video image translation process for obtaining numeric data was undertaken in seven steps using open-sourced algorithm codes as referenced. The steps were, 1) Image extraction, for a sequence of image frames each with

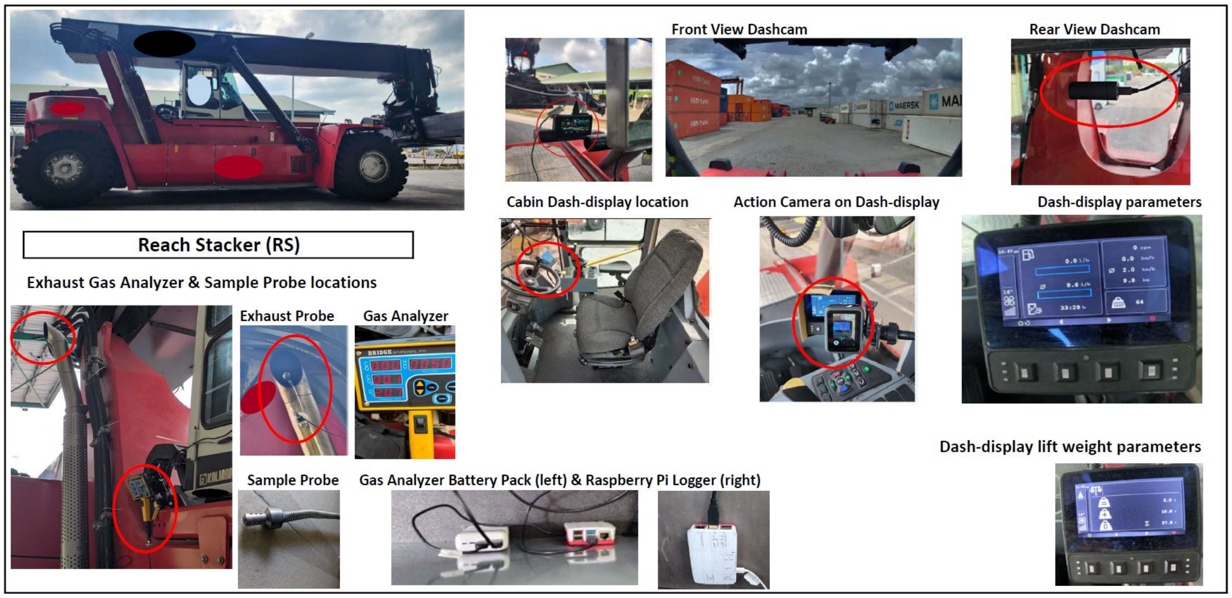

Fig. 1. Sensors system devised and installed on the Reach Stackers

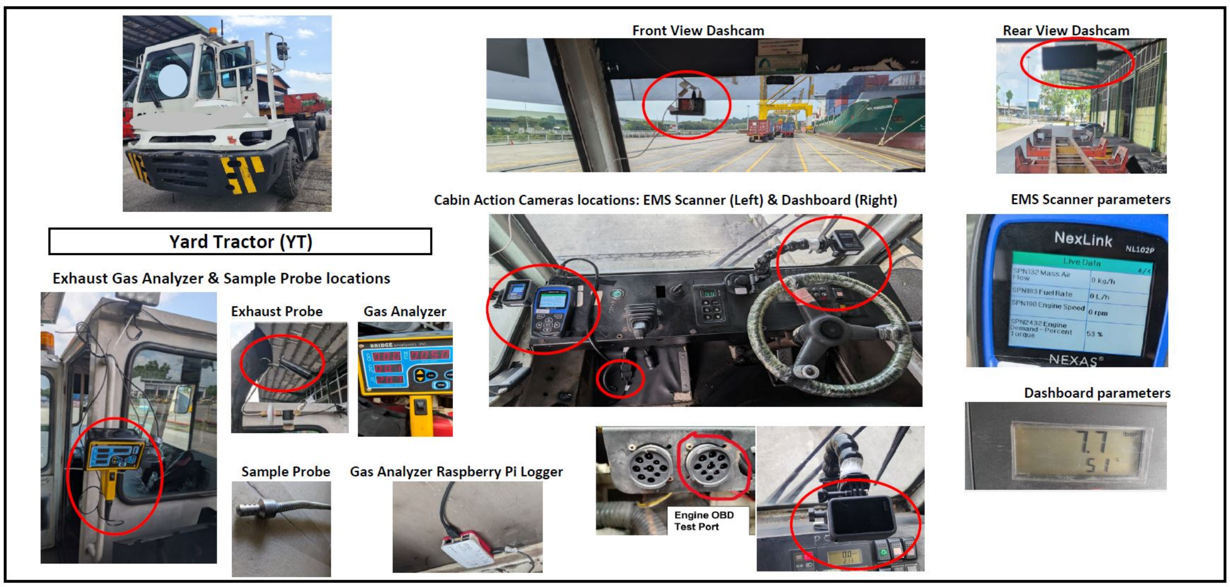

Fig. 2. Sensors system devised and installed on the Yard Tractors.

reference timestamps, using [14]. The frame rate was determined by, and the total number of frames was obtained from using [15]. 2) Object Detection, to detect the image focus area, each extracted frame was analyzed using an object detection algorithm from [16], and a custom trained YOLOv8 algorithm was used to detect the display screen image areas, [17], [18]. 3) Region of Interest (ROI) extraction, YOLO models are trained to detect an entire object rather than an objects sub-image, therefore color filtering was used to extract sub-imagery from the regions of interest and converted to Human Visual System (HVS) color space [19]. To facilitate extraction color-based segmentation enabled the cropping of images for the required information. 4) Detailed Cropping, A detailed cropping step was applied to the previous ROI extraction step to orientate and extract more specific areas of interest. 5) Image Processing, was then used to improve the image quality for text recognition software. Each cropped image required several processing steps to ensure readable text that maximized the data extraction accuracy. This processing was dynamically adjusted for each frame based on the original image characteristics by using grayscale conversion [19], applying levels of gray thresholding [20], swapping black and white pixels using [21], and removing white noise around characters using [22], together with reinforcing of the characters structure

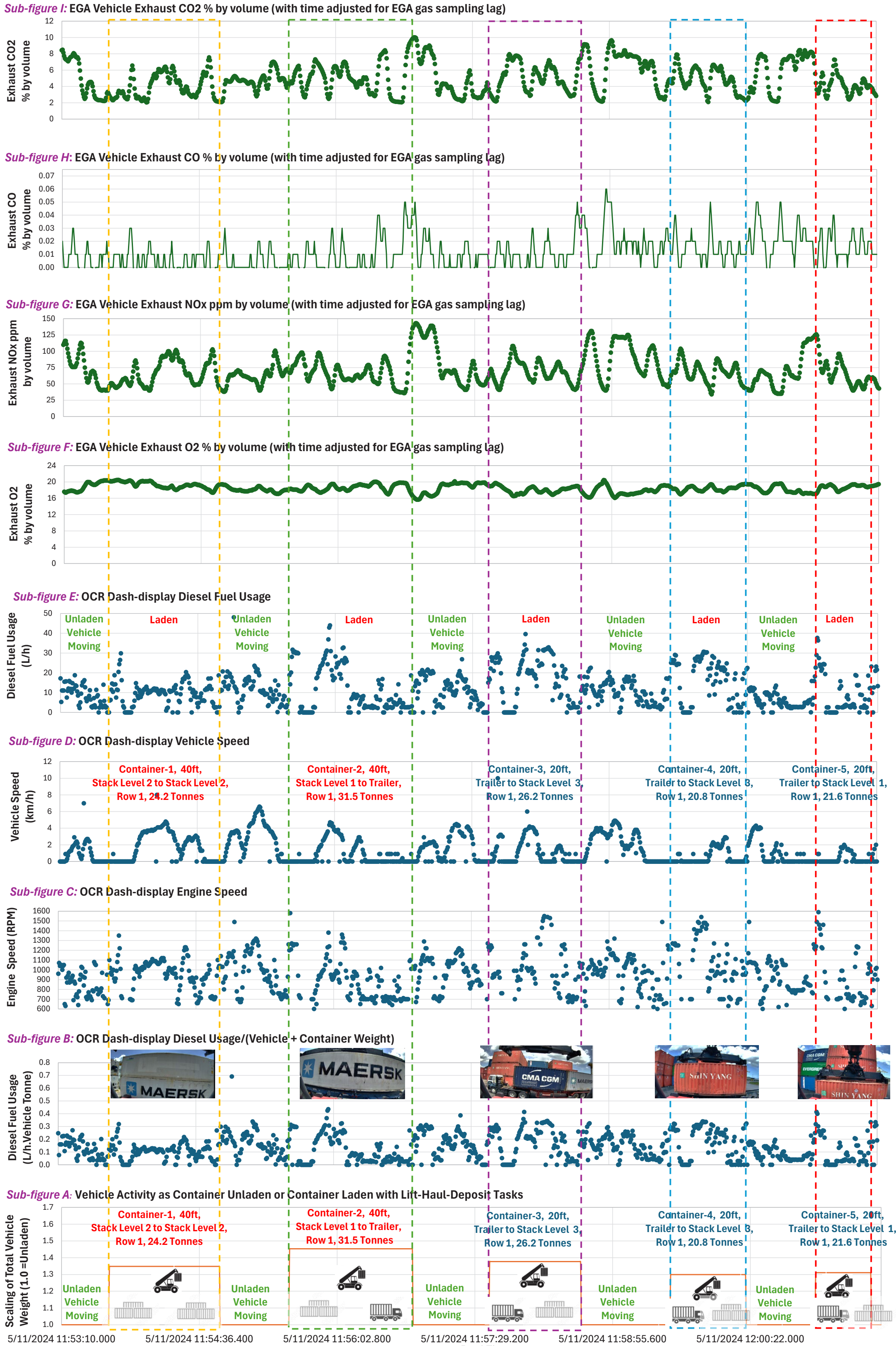

Fig. 3. Examples of the sensor system combined EGA-OCR-Dashcam (Front) time-series port trial results for a Reach Stacker.

and connecting any broken components using [22]. 6) Optical Character Recognition (OCR), the pre-processed images were then data extracted using pytesseract [23], [24]. A custom OCR configuration limiting the recognition to digits and special characters was used to improve the recognition accuracy [25]–[27]. Binary thresholding was applied using [26], to control the text contrast from its background, and by conversion into either white or black based on a threshold range. The extracted data was then listed in a CSV file with its reference frames and temporal ordered timestamps. In 7) Manual Verification and Refinement was undertaken with the extracted CSV file data manually checked against the video extracted images with any poor results re-run through steps 3, 4 and 5 by using adjusted settings. The first OCR run had an average correction requirement for 22% of its dataset, reducing to 15% in a second run, which was still a significant quantity of data to manually review.

Therefore a disadvantage of this study's approach was the significant time and effort required for the OCR data processing, although these times would be reduced in future trials by using the learnings' to improve the process and software tools. Importantly, the study approach key advantage is that it has delivered a practical and quickly deployable sensor system for obtaining real vehicle duty-driving time profile data. This was achieved with minimal intrusion on port and vehicle operations for the example results shown in the next Section V.

V. Port Trials Example Results & Discussion

Figure 3 has nine sub-figures A to I showing the monitored duty-time profiles for a Reach Stacker over a sample period of 8.5 minutes, at 0.5 sec time increments. The results data from the EGA is in the top four sub-figures F to I with the green lines, then the OCR data is in the middle four sub-figures B to E with blue lines. At the bottom is sub-figures A and B showing the front dashcam information for the vehicle activities together with the Reach Stacker dash-display reported container weight sourced from the OCR translation dataset. The container types, sizes, general location movements with duty periods are shown in Figures 3 - A and B, with example front dashcam images in Figure 3 - B.

The Reach Stacker laden and unladen periods are shown in Figures 3 - A, - D and - E, with colored vertical dash lines to highlight the laden activities for moving two 40ft and then three 20ft containers. The larger size, weight and bulk of the 40ft containers take longer to move than the 20ft containers irrespective of the container pickup and deposit heights, Figure 3 - A. In Figure 3 - E not unexpectedly shows the greater peak fuel usages associated with the heaviest container movements, which are typically up to double the fuel usage of that for the unladen vehicle. Typical fuel usages lie in the range of 10 to 20 Litres/hour for both laden and unladen activities. The vehicle speeds in Figure 3 - D for container haulage show a repeatable consistency between the laden and unladen periods. Notably the OCR sourced fuel usage, vehicle speed, and engine speed (indicating the the engine loading) have repeatable and aligned profiles across the Figures 3 - C to E. Engine idling periods are shown by the minimum engine speeds of 600 to 700 rpm in Figure 3 - C. Notably the moving of Container-3 (20ft size and 26.2 Tonnes) from a trailer to the highest yard stack level of three containers high (Figure 3 - A) shows the associated peak engine loading and fuel usage in Figure 3 - C and E. The derived metric for fuel usage per vehicle total weight in Figure 3 - B, shows peak usages whilst laden are not significantly greater than the unladen periods. This is indicative of the minimum energy required to move a Reach Stacker of 69.5 Tonne service weight, which for example increases by 45% when laden with Container-2 at 31.5 Tonnes, Figure 3 - A.

The monitored exhaust gas profiles within the group of Figures 3 - F to I have alignment in their peaks and troughs with each other over time. Some of these features align with the OCR dataset profiles in Figures 3 - C to E, although generally the EGA data peaks appear to lag those for the OCR, which is indicative of the time lapse between the engine activities through to the resulting exhaust gas profiles. Notably the CO2, CO and NOx peaks shown in the center and ongoing into the right side of Figures 3 - G, H and I coincide with vehicle activity changes across the Figure 3 profiles.

Therefore the port trials of the sensor system has proved its practical deployment with results that characterize the duty-time profiles of selected container handling equipment activities on a seconds time basis. The profiles provide referenceable data for predicting fuel usages and emissions by activity task based on the trials monitored parameters. These predictions by activity task also then define the business-as-usual baseline scenarios, which are both vehicle fleet scalable and applicable to most container ports. These baseline results will then enable comparisons with the predicted performances for vehicles using alternative fuels and power-drives that are being considered for decarbonising ports.

VI. Conclusions

This paper presents a variant on heavy duty vehicles combined PEMS and PAMS by including action cameras to monitor and record port container handling equipment display screen information. The developed sensor system and setup was deployed through in-port trials to reveal container handling equipment duty and driving profiles that include real-world factors. This paper's results present a Reach Stackers time-series profiles for its diesel engine loading, vehicle speed, fuel usages and exhaust emissions, together with operational duties on very short time scales that capture the representative characteristics. These duty-time profiles also provide baseline data for predicting and assessing the potential for reduced diesel usage and exhaust emissions through assessing port decarbonisation options.

In summary, this study has devised a portable, deployable, and flexible IoT-Enabled PEMS–PAMS-camera monitoring system for ports container handling equipment. The systems sensors, monitoring approach, trials methodology, and data collection, with analysis tools form the basis for an IoT device. A learning is that the OCR tools need refinement to reduce the data processing times. Based on the port trials the sensor system approach can be deployed in other ports and is adaptable to other types of container handling equipment.

ACKNOWLEDGMENT

This project and trial results were made possible by the access to the Senari Container Port provided by the Kuching Port Authority, Sarawak, Malaysia. We specifically thank their management and facilities staff for their commitment, expertise, and time contributions whilst also operating a busy port. We acknowledge Swinburne University of Technology Sarawak and Basil TungLiong Wong for their support, plus Steven Percy from Swinburne University of Technology, Melbourne and Jenny Hayward from CSIRO for co-supervising this project. D. Holder and S. Mullanu have received PhD scholarship funding from the Australian Governments Research Training Program with Swinburne University of Technology Research Investment Funding, provided under the Victoria State Education Department. Further scholarship funding has been provided by the Future Energy Exports Cooperative Research Center under the Australian Government Department of Industry, Science & Resources Cooperative Research Centers Program.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CREDITS

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