

A quality control system for logistic ports goods movable harbor cranes based on internet of things and deep learning

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Article Info

Article history:

Received Oct 24, 2023

Revised Nov 5, 2023

Accepted Nov 14, 2023

Keywords:

Deep learning

Goods moveable harbor crane

Industrial internet of things

Long short-term memory

Recurrent neural network

ABSTRACT

The growth of commercial activity and the transportation of goods around the world has increased the challenges of stevedoring within ports. In case of loading and unloading ships safely, quickly, and efficiently, goods movable harbor cranes play an important role. This work aims to propose an industrial internet of things (IIoT)-based quality control system for logistic services ports goods movable harbor crane (QC-GMHC). The GMHC system based on using programmable logic controller (PLC), along with a multi-sensor data collecting system. Several operations have been done to establish the QC-GMHC system as: GMHC sensors real-time data storage, and data sharing; monitoring the GMHC status (remote-local); and the efficiency reporting. In order to validate the proposed system's hardware, it was used in an already operational GMHC for six months, during which data were collected and analyzed. The results revealed that the proposed hardware system worked efficiently for 24 hours. To forecast the efficiency of the GMHC, a deep learning (DL) conventional long short-term memory (LSTM) and neural network model was trained and validated using synthetic data generated from acquired real data. The results showed that QC-GMHC can calculate efficiency with an accuracy of 80%, which is sufficient for our application.

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1. INTRODUCTION

In recent years, internet of things (IoT) has attracted a lot of attention from both academics and business leaders [1]–[3]. The integration of IT with industrial automation and control systems gave rise to the concept of industrial IoT. However, while IoT was designed for businesses, industrial IoT (IIoT) was aimed at manufacturers [4]–[6]. IIoT technology makes it possible to integrate several sources of information, such as sensor readings, user comments, the knowledge and resources of service providers, and more, in order to give timely and effective replies. This is how the next industrial revolution, often known as the age of industry 4.0 or the industrial internet of things is influencing technological development [7], [8]. IIoT focuses on complicated physical machinery that is coupled with industrial sensors and its relevant software, as opposed to IoT, which connects physical things through wired and wireless network. For a flawless system, the industrial internet of things not only connects machines but also includes a human interface unit [9]–[12]. Logistics services include goods movable harbor cranes (GMHC) in significant amounts. Managing the

movement of commodities between the place of origin and the point of consumption to satisfy the needs of businesses or customers is known as logistics. Ship loading and unloading is the primary function of the GMHC. The performance and efficiency of loading and unloading can be affected by poor monitoring system and missing performance indicator [13]. Calculating the efficiency rate helps in making correct decisions for raising the production rate, improving maintenance quality and reducing operating costs.

Intelligent manufacturing processes cannot be developed without data modeling, labeling, and analysis. Therefore, to overcome the operation problems that face the goods movable harbor crane, artificial intelligence (AI) techniques can be used. One of the most famous techniques is deep learning method. Deep learning (DL) method can transform factories into cutting-edge, AI-powered smart hubs, improving efficiency across the board [14]–[16]. The industrial sector, for instance, may benefit from DL techniques that help extract intelligence from murky sensory data in order to facilitate intelligent production. Feature learning in DL is done automatically and without human interaction, which is one advantage over more traditional machine learning methods [17]. The benefits of DL methods include the ability to automatically learn from data, detect patterns, and arrive at sound conclusions. Recent developments in DL methods have made it possible for IIoT networks to evolve into highly efficient infrastructures [18], [19].

In order to successfully operate the GMHC, several working parameters have been used as payload type, working hours, sweeping hours, payload weight, sweep weight to estimate the crane efficiency. According to the efficiency: the operation costs can be reduced, customer demand can be predicted, productivity can be increased, downtime can be minimized, new insights into markets can be gained, and valuables can be extracted from operations thanks to DL in IIoT [20]–[22]. Therefore, a storage smart system can be used as the long short-term memory (LSTM) [23]. Memory blocks are specialized units found in the LSTM architecture's recurrent hidden layer. The memory blocks incorporate both specialized multiplicative units called gates for controlling data flow and memory cells with self-connections for storing the dynamic state of the network over time.

Every memory unit in the first design was equipped with both an input and an output gate. The input gate controls the transmission of input activations to the memory cell. The activations of cells are channeled throughout the network after passing via the output gate. The memory block eventually got the forget gate [24], [25]. Adaptively forgetting or resetting the cell's memory, the forget gate scales the internal state of the cell before adding it as input through the cell's self-recurrent link [26]–[29].

The aim of the proposed study is to propose an industrial internet of things-based quality control system for logistic services ports goods movable harbor crane (QC-GMHC). The GMHC system based on using programmable logic controller (PLC), along with a multi-sensor data collecting system. To forecast the efficiency of the GMHC, a DL conventional LSTM and neural network model was trained and validated using synthetic data generated from acquired real data.

The following outline describes the paper's structure: the following section discusses previous research and the current issue at hand. After then, existing system components and limitations are presented in section 3. The proposed method is unveiled in section 4. The experimental work and findings are presented in sections 5 and 6, and the QC-GMHC efficiency prediction model, results, discussions, and conclusions are presented in sections 7, 8, and 9, respectively.

2. LITERATURE REVIEW

PLC and human machine interface (HMI) are used to control and monitor our GMHC. There is no work efficiency coefficient in this system. The lack of a GMHC performance indicator causes a slew of issues, including increased failure rates, high operating costs, and increased fuel usage. Many studies have been conducted on the crane monitoring system in order to improve the safety and reliability of goods movable harbor cranes. These investigations were primarily concerned with information exchange, system integration, and visualization [30]. Radio-frequency identification (RFID), Zig-Bee, Wi-Fi, 5G, and other information communication technologies were used in various crane monitoring systems.

Lee *et al.* [31] discussed the development of a new tower crane operating system that uses wireless control video and RFID technologies to improve communication efficiency between workers and crane operators. The paper included a literature review of tower crane research, a description of the new system, a case study to evaluate its efficiency, and a discussion of the results and future work. The case study showed that the new system improved work speed, communication efficiency, safety, and communication satisfaction.

However, there were still some obstacles to overcome before the system can be commercialized, such as read errors in RFID technology and difficulties in supplying power to wireless devices. Gao *et al.* [32] have presented a wireless microelectromechanical system (MEMS)-based swing angle measurement system for industrial crane systems. The system is made up of two wirelessly communicative attitude heading reference system (AHRS) sensor units that are installed on the crane's base (or jib) and hook

(or payload), respectively. To estimate the intended orientation of the payload and the base, the conventional extended kalman filter (EKF) is utilized in conjunction with a three-axis accelerometer, three-axis gyroscope, and three-axis magnetometer. Together with the given physical characteristics, the two measured orientation parameters may be used to compute the payload's swing angles. The swing angle measurement method that was created is inexpensive and simple to integrate into actual crane systems.

For the purpose of monitoring construction equipment safety, Yang *et al.* [33] have created an intelligent monitoring system based on multi-sensor technology. Numerous sensor clusters, data management and signal transmission systems, condition assessment, identification, and warning systems make up the system. The primary focus of the article was on each system's data integration, transmission, and processing. The system is capable of automatically transforming the initial data gathered by several sensors and feeding it into the assessment modules to show and track the structural health status of construction machinery. The paper also presented a case study of the system mounted into a tower crane.

Shi *et al.* [34] have described the design of a structural health monitoring system (SHMC) for large-scale cranes using narrow band IoT (NB-IoT) technology. The system consists of three components: a monitoring terminal, a wireless transmission module, and a core monitoring platform. The monitoring terminal collects external signals to monitor the crane information in real time. The wireless transmission module uses NB-IoT to transmit the data to the core monitoring platform. The core monitoring platform parses and calculates the data, and stores it in a database. The system's implementation utilizing Alibaba EC2 instance hosting Kafka, Apache Storm cluster, and Alibaba web services is also covered in the paper. In order to guarantee safe operation, the system can identify problem information and track the operational state of cranes in real time.

The potential of 5G wireless communication technology in the manufacturing sector, namely in human-machine and human-robot interaction, has been covered by Longo *et al.* [35] in three industrial use scenarios. In order to maximize network quality and the pace at which digital technologies are accepted in the shop floor, the study suggests a quality of service (QoS)/quality of experience (QoE) model to guide the deployment of 5G-assisted solutions for operator 4.0. The article also examines how 5G may offer the network infrastructure required for the future factory's human-machine symbiosis. The paper provides background information on 5G technology and its features and benefits. Finally, the paper proposes to assess HMI/human-robot interaction (HRI) applications based on a measure of QoE.

Singh *et al.* [36] have described the benefits of industry 4.0 and the industrial IoT in improving the reliability of various industries throughout the world through remote monitoring of critical systems in overhead cranes using wireless sensor networks. The paper presents two configurations for acquiring and transmitting data wirelessly to a remotely-located cloud server for analysis, and demonstrates their successful implementation through a workshop simulation and test setup. The paper also highlights the importance of data security in these configurations. The Table 1 summarizes the contributions and comments of previous researches.

2.1. Contributions

The study contributions can be listed as: i) new hardware and software systems to improve the efficiency of the goods movable harbor crane (GMHC). ii) To our knowledge there is no sufficient research papers related to the same field. iii) Reducing the operation costs, predicting the customer demand, increasing the productivity, and minimizing the down time.

3. EXISTING SYSTEM COMPONENTS AND LIMITATIONS

The current system components can be listed as follows:

- i) Sensors, two types of sensors have been used like:
 - Weight sensor: after being sent to the PLC, the analog signal was scaled by the signal conditioning unit of the PLC to make it appropriate for the analog-digital converter (ADC). The load weight is then determined by processing this signal using the PLC program's system equations.
 - Angle position sensor: it's a variable resistance that varies according to the crane boom's angle. The PLC receives the analog signal, which is then scaled by the signal conditioning unit to make it appropriate for the ADC. The angle of the crane boom is then determined by processing this signal using the PLC program's system equations.
- ii) PLC (S5-Siemens): the siemens PLC type with serial communication is S5-928B.
- iii) HMI screen: it is connected to the PLC for monitoring the net weight, max. weight, and the radius. The system operation can be described as: the operator controls the GMHC movements such as hoisting, slewing and luffing by using joysticks. These control joysticks are connected to PLC as digital inputs, and then the PLC can control the movements of the motors. The HMI screen displays net weight, max. weight

and the radius for the operator only, then, based on these readings, the operator makes his decisions to control the GMHC.

Table 1. Summary of the contributions and comments on the historical researches

S. No	Authors	Contributions	Comments
1	Lee <i>et al.</i> [31]	Suggests a new tower crane operating system that will increase the effectiveness and security of tower crane operation by utilizing RFID and wireless control video technologies.	The commercialization of the system is still remote due to constraints that hinder improvements in system efficiency, such as the limitations of RFID technology and the difficulty of supplying power to wireless equipment.
2	Gao <i>et al.</i> [32]	Proposes a wireless ZigBee wireless communication system with MEMS sensors to determine swing angle in crane systems utilizing AHRS.	Includes the need for calibration in real industrial environments to obtain the same level of accuracy achieved in the lab, and the potential for signal disruption from MEMS devices in actual manufacturing environments.
3	Yang <i>et al.</i> [33]	Covers multi-sensor-based safety monitoring of construction equipment, including intelligent monitoring system integration approaches for long-span bridge soundness, risk assessment, identification and warning systems, and condition evaluation. It also includes references to related projects and studies.	The paper only focuses on introducing the working principle and integration mechanism of systems for multi-sensor-based safety monitoring of construction equipment.
4	Shi <i>et al.</i> [34]	Outlines the design of a narrow band IoT-based structural health monitoring system for large-scale cranes. The system can detect problems and track the operational state of the cranes in real-time to guarantee safe operation. Additionally shown is the design's implementation using the Alibaba EC2 web server, Kafka server, and Apache storm cluster.	The structural health monitoring system of the crane (SHMC system) is still under development and has not yet been fully tested in real-world conditions.
5	Longo <i>et al.</i> [35]	Argues that 5G will revolutionize the way that humans and machines interact in the manufacturing sector. It also suggests a QoS/QoE model that will guide the deployment of 5G-assisted industry 4.0 solutions, increasing network quality and the adoption rate of digital technologies on the shop floor.	The paper provides a positive outlook for the future of 5G-based industrial IoT. However, it is important to be aware of the potential limitations and challenges that may need to be addressed before this technology can be widely adopted.
6	Singh <i>et al.</i> [36]	Presents two configurations for acquiring and transmitting data wirelessly to a remotely-located cloud server for analysis. It also highlights the benefits of industry 4.0 and the industrial internet of things in improving the reliability of various industries.	The paper does not provide a detailed analysis of the cost-effectiveness of the presented configurations for remote monitoring. Additionally, the paper does not discuss potential ethical or privacy concerns related to the collection and transmission of data from critical systems.

The current system limitations can be summarized as follows:

- i) Poor monitoring system: the current control system is simple and does not have many details because the HMI screen displays only the net weight, maximum weight and the radius. Therefore, it is needed to monitor all the data of the GMHC remotely or from the GHMC operator cabin, as well as, help in making the communication between the GMHC and the decision makers.
- ii) Missing performance indicator: the absence of the performance indicator for the GMHC system, which is considered as an indicator for the GMHC productivity. This can be achieved by taking into account the working hours, sweeping hours, total payload of the ship and payloads type. This may lead to many problems, such as increased failure rate, high operating cost and the fuel consumption. Calculating the efficiency rate helps in making correct decisions for raising the production rate, improving maintenance quality and reducing operating costs. Finally, this study proposes a smart QC-GMHC system including radial neural network (LSTM-RNN), to calculate the work efficiency of the goods movable harbor crane. Which is considered as an extension of the system for monitoring status of goods movable harbor crane in [37].

Instead of using a graphical processing unit (GPU), we decided to implement the LSTM RNN architectures on a multicore central processing unit (CPU). The choice was decided because CPUs may be used in clusters with inexpensive hardware and have relatively easy implementation complexity and debugging requirements. The proposed system in this study is considered as the first system to discuss the smart QC-GMHC system including LSTM-RNN to calculate the work efficiency of the goods movable harbor crane. There is no similar researches to compare the outputs of this work with them.

4. THE PROPOSED QC-GMHC SYSTEM

The crane system in the current study is used to unload the goods in a slightly different way from the other systems, as the goods are completely placed inside large containers as in Figure 1, which shows the unloading Figure 1(a) and sweeping in Figure 1(b). The crane lowers the load by taking a handful of goods each time using the crane rams until it finishes the payload. At the end of the payload there remains a quantity of scattered goods that we cannot download, in this case the crane waits until this quantity is collected together and unloads it, this process takes a different time in unloading and is called the sweeping process. Both unloading and sweeping time should be considered. This paper presents an IIoT based quality control system for logistic services ports GMHC so called QC-GMHC. It can calculate the efficiency of GMHC per ship considering payload type, working hours, sweep hours and total payload weight.

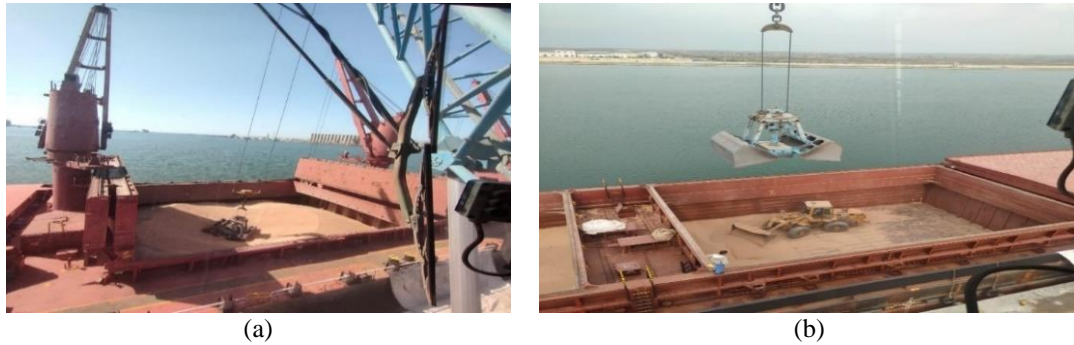


Figure 1. Logistic service ports goods movable harbor crane used in current study (a) unloading and (b) sweeping

A particularly promising remedy for issues relating to sequences and time series is the use of LSTMs, it works very much like an RNN cell. Each of the three components of the LSTM, as shown in Figure 2, has a distinct purpose. The first section decides whether the data from the previous timestamp should be remembered or if it is unnecessary and can be ignored [38].

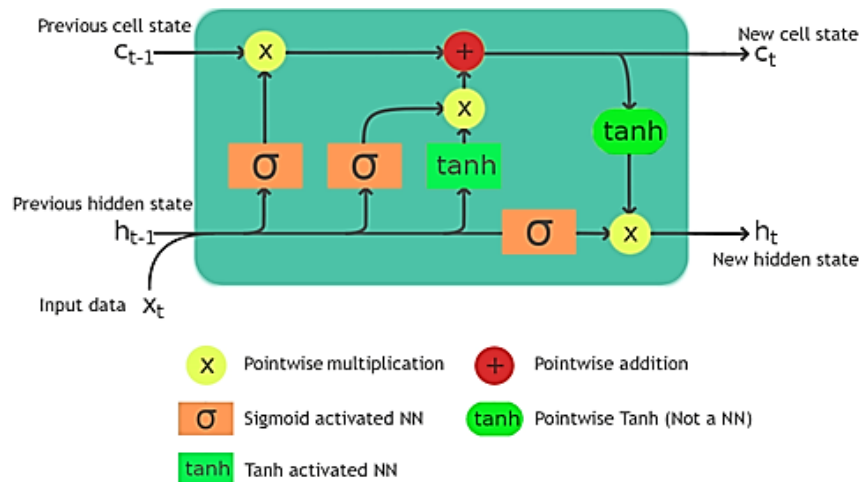


Figure 2. LSTM layers structure

The cell attempts to learn new information from the input to this cell in the second section. The cell finally transmits the updated data from the current timestamp to the next timestamp in the third section. The three components of an LSTM cell are referred to as gates. Forget gate is the name of the first component. Input gate is the name of the second component. Output gate is the name of the last component. Just like a simple RNN, an LSTM also has a hidden state where H_{t-1} represents the hidden state of the

previous timestamp and H_t is the hidden state of the current timestamp. In addition, LSTM also has a cell state represented by C_{t-1} and C_t for previous and current timestamp respectively. In forget gate a cell of the LSTM network, decide whether the information from the previous timestamp should be kept or forget it.

$$f_t = \sigma(x_t * U_f + U_{t+1} * W_f) \quad (1)$$

Where U_f is weight associated with the input, W_f is the weight matrix associated with hidden state, U_{t+1} is the hidden state of the previous timestamp and x_t is input to the current timestamp. Later, a sigmoid function is applied over it. That will make f_t in (0,1). This f_t is later multiplied with the cell state of the previous timestamp as shown in (2) and (3).

$$C_{t-1} * f_t = 0 \quad \text{if } f_t = 0 \text{ (Forgot everything)} \quad (2)$$

$$C_{t-1} * f_t = C_{t-1} \quad \text{if } f_t = 1 \text{ (Forgot nothing)} \quad (3)$$

If f_t is 0 then the network will forget everything and if the value of f_t is 1 it will forget nothing. In input gate, it quantifies the importance of the new information carried by the input.

$$i_t = \sigma(x_t * U_i + U_{t+1} * W_i) \quad (4)$$

Where U_i is the weight matrix of input, W_i is the weight matrix of input associated with hidden state, U_{t+1} is a hidden state at the previous timestamp, and x_t is an input at the current time stamp t . In addition, sigmoid function has been applied the the final result. As a result, the value of i at timestamp t will be between 0 and 1.

Now the new information that needed to be passed to the cell state is a function of a hidden state at the previous timestamp $t - 1$ and input x at time stamp t . The used activation function is (\tanh). The value of the new information will range from -1 to 1, due to the tanh function. Information is either deducted from the cell state if the value of N_t is negative or added to the cell state at the current timestamp if the value is positive.

$$N_t = \tanh(x_t * U_c + U_{t-1} * W_c) \quad (5)$$

The output gate's function can be divided into the following three steps (6) to (8):

- After applying a function to the cell state, creating a vector O_t to scale the results in the range of -1 to +1.
- Making a filter that can control the values which must be produced from the vector established previously using the values of H_{t-1} and x_t . The sigmoid function is used in this filter once again.
- Adding this regulatory filter's value to the vector produced in step 1 and transmitting it as an output as well as to the following cell's hidden state.

$$O_t = \sigma(x_t * U_o + U_{t-1} * W_o) \quad (6)$$

$$H_t = O_t * \tanh(C_t) \quad (7)$$

$$\text{Output} = \text{Softmax}(H_t) \quad (8)$$

5. THE QC-GMHC SYSTEM ARCHITECTURE

Figure 3 displays the composition architecture of the monitoring system that is suggested in this study. To complete the data collection, saving, interaction, and QC processing, the hardware system's multi-type sensors (weight, angle position, and proximity sensors, among others) gather the GMHC's status data and the data from the surrounding environment. The data is then uploaded via a serial port to the monitoring system information system (PC). To complete the crane's operating duty, the GMHC control system receives scheduling commands from the software platform (IoT server) and sends them to each terminal actuator.

In the information system, data is processed via open platform communication (OPC) server and LabVIEW program for analysis and reviewing. Further, data is transmitted to an IoT cloud server "Thing Speak Channel" and efficiency report preparation and publishing. Technical staff can see data charts on the monitoring system software platform to view the current GMHC operation data and the operating posture of the equipment while interacting with the IoT cloud server.

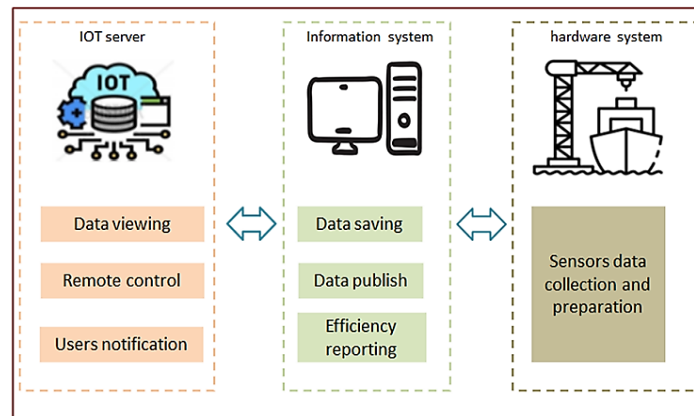


Figure 3. QC-GMHC system architecture

5.1. System components description

- Sensors
There are many sensors in the crane, including analog and digital such as weight sensor, angle position sensor and proximity sensors.
- PLC (S5)
The crane's movements are managed by a siemens PLC of type simatic S5 equipped with CPU 928b, which also collects data from the crane via any kind of serial communication.
- OPC sever program
NI OPC server 2016 V5.19.492.0 is used to communicate with the PLC.
- LabVIEW program
Data is sent to the Arduino from the OPC server using NI LabVIEW 2015 V15.0.1.
- Arduino Mega 2560
The Arduino IDE program is used to program this device to transfer data from the LabVIEW application to the ESP-32s Wi-Fi module.
- Arduino micro-SD card module
Utilizing the SPI interface in conjunction with a microcontroller system and a file system driver, the micro-SD card Adapter module reads and writes data to micro-SD cards. Arduino users may utilize the Arduino IDE, which comes with an SD card, to initialize and read-write library cards directly.
- ESP-32s Wi-Fi module
Using the Arduino IDE software, this tool is configured to receive data from the Arduino and sent it to the thing speak channel.
- Arduino IDE program
The Arduino mega and the ESP-32s Wi-Fi module are programmed using the Arduino IDE V1.8.13.
- Thing speak channel
Utilizing this channel, data is stored for use in tracking the goods movable harbor crane.
- Personal computer (PC)
To be working in this research, the following applications have been installed: OPC server, LabVIEW, and the Arduino IDE.

In the hardware system, the system consists of two parts, the first part is the PLC system, which controls the movement of the GMHC and sensors data collection. There are many sensors in the GMHC, including analog and digital such as weight sensor, angle position sensor and proximity sensors. The second part is the system that was developed in [37]. The two parts have been combined together to reach an integrated system for monitoring and controlling the GMHC, as shown in Figure 4. Figure 4(a) illustrates the work flowchart of the proposed system, while Figure 4(b) illustrates the system components. PLC will be serially linked to a PC running LabVIEW software and the NI OPC “National instruments open platform communications” server. The Arduino controller is linked to this PC. The “ESP-32s” Wi-Fi module is serially linked to this controller, and the Wi-Fi module uploads the data to the internet of things server. The OPC sever program is used to read data from the PLC by means of serial connection, as seen in Figure 4. Data from the LabVIEW software is sent to the ESP-32's Wi-Fi module via an Arduino mega that has been designed to do so. The Arduino and the micro-SD card adapter module are linked. Data from the

Arduino is sent to the IoT server via the ESP-32s Wi-Fi module, which is configured using the Arduino IDE software. Through this server, data is kept in order to monitor and operate the crane. For usage in this study, a PC has been configured with the following software installed: OPC server, LabVIEW, and the Arduino IDE. The following are the GMHC specifications: part no: HMK 260E; maximum weight: 45 tons; maximum radius: 42 meters; minimum radius: 10 meters.

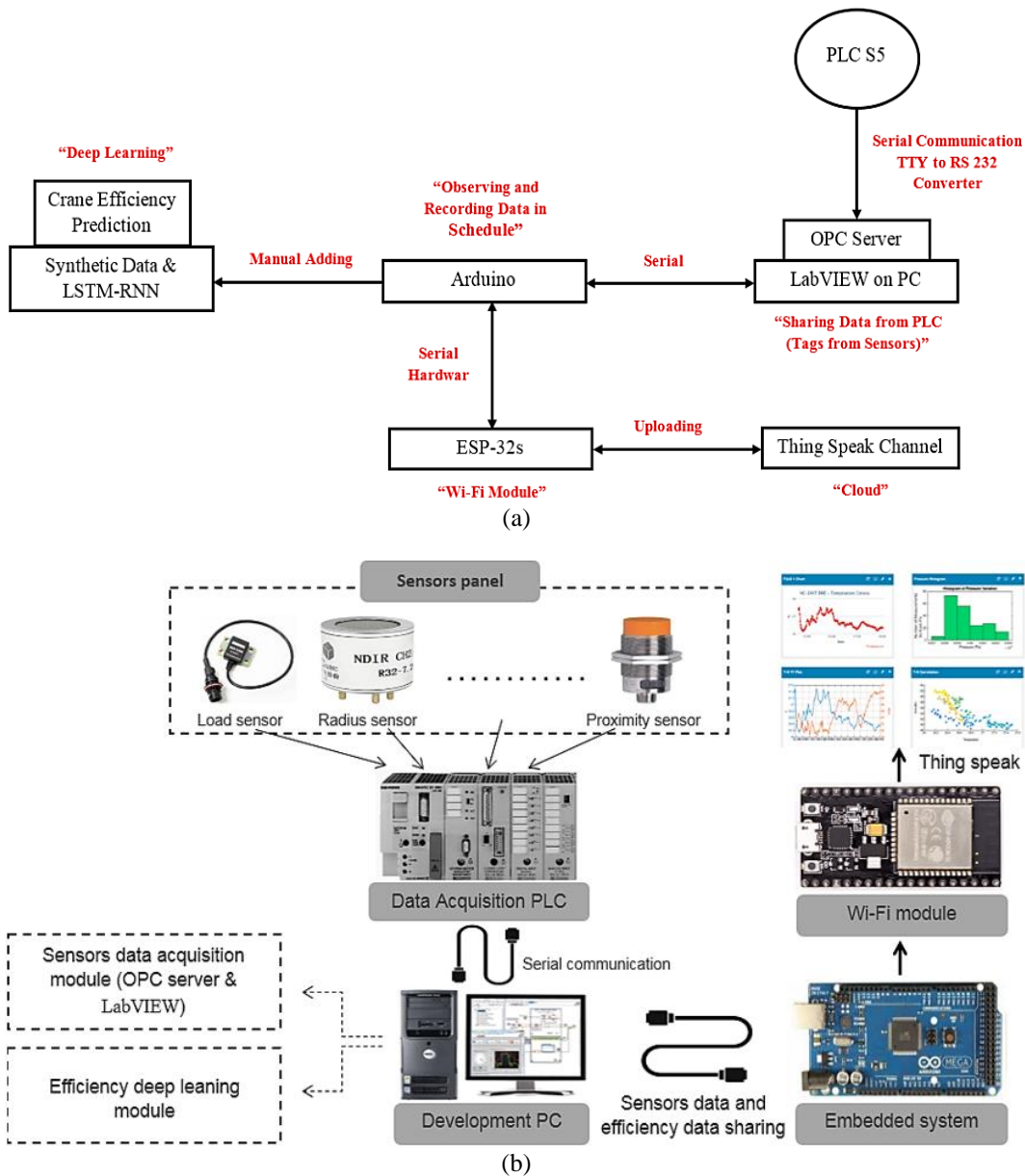


Figure 4. The proposed system components description (a) work flowchart and (b) system components

5.2. Crane efficiency model

The basic principle of crane efficiency predictors based on DL is shown in Figure 5. After knowing the output (efficiency measure) and the corresponding input features such as actual working hours, stopping hours, number of faults, rate of crane loads per ship, type of crane loads; data prepared for synthetic data (training and test) generation, then deep learning LSTM-RNN can be employed and trained using synthetic training data. Further, model can be validated using synthetic test data. Original data is used as new data to evaluate the system.

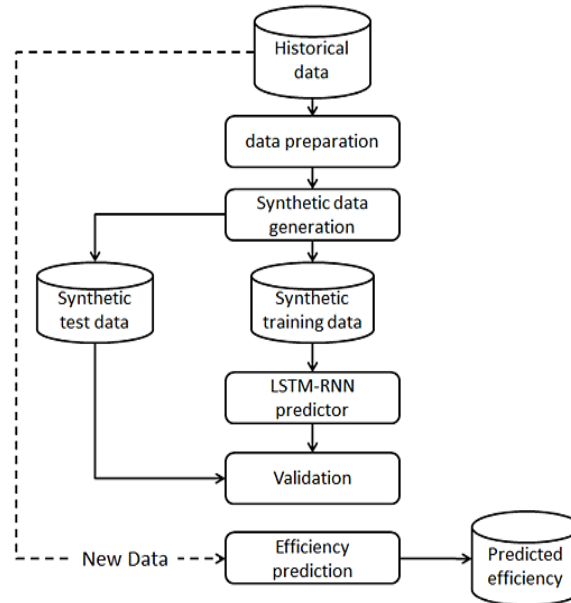


Figure 5. Principle of deep learning based crane efficiency prediction model

6. RESULTS

6.1. Experimental field setup

In order to verify the proposed system, the system components have been installed in real time on GMHC in damietta port, Egypt as shown in Figure 6 for a period of six months. Table 2 shows a sample of the collected data. The payloads that the crane dealt with are of same type for the same payload, but their type differed from one payload to another.

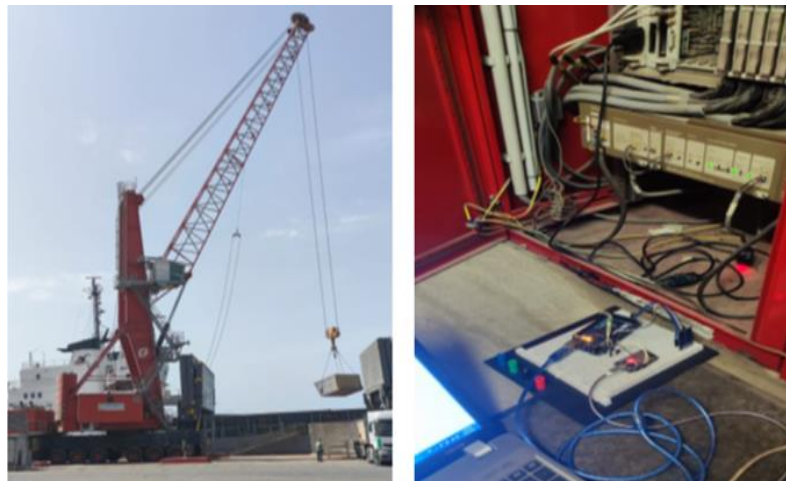


Figure 6. The QC-GMHC physical platform

It is necessary to specify the type of load (WL) (scrap-phosphate-seeds-wheat-beans-corn) and the total quantity for one payload (TP). Each load took a different period of time in loading from the other types, so it was necessary to record the time period for each load at the end of the day (WH). Each payload came in large quantities, and the crane would not finish this amount in one day, so it was necessary to record the loads carried out by the GMHC on a daily basis. Besides, it was necessary to know the ideal load per hour for each type (OPPH). For example, in the scrap vessel on 5/7/2021, crane loaded scrap WH for 19 hours and ideal quantity OPPH was 80 tons per hour, i.e., 1520 tons, but in practice, the GMHC loaded only 1,000 tons then.

All previous items had been collected upon completion of the entire payload and not for one day. At the end of each payload, a lost part of the load remained, which took time to load, so it was recorded separately and was called the sweep, and its quantity (SP) and the time (SH) it took was then subtracted from the total payload (TP). After a period of six months, we recorded 26 payloads of different payloads types loaded in 110 days. The loading efficiency had to be calculated manually, as Table 2 was modified and new columns have been added to calculate the efficiency, which are as (9):

$$EFF = (TP - SP) / (OPPH * (WH - SH)) \tag{9}$$

where, SH is the number of sweep hours, WH is the total number of hours, SP is the quantity of the sweep, TP is the total payload, and OPPH is the ideal quantity per hour. For example, in the scrap boat from 05/07/2021 to 07/07/2021 efficiency calculated as following:

- The number of loading hours without sweep (WHWS=WH-SH), for example in the scrap boat from 05/07/2021 to 07/07/2021. The number of loading hours (WH=59) hours and the number of sweep hours (SH=8 hours). The number of loading hours without scanning becomes (WHWS=51 hours), and so on.
- The quantity of the payload without scanning (TPWS=TP-SP), as in the previous example of scrap, TP=3,000 tons and SP=300 tons, so TPWS=2,700 tons.
- The ideal quantity that he payloads (OPTP=OPPH×WHWS), as in the previous example of scrap, OPPH=80 tons and WHWS=51 hours, so OPTP=4,080 tons.
- EFF (%) efficiency=TPWS/OPTP, as in the previous scrap example, TPWS=2,700 tons and OPTP=4,080 tons, so the EFF (%)=66.2%.

After modifying and adding the previous elements, the data has been modified to become as in Table 3. Where the number of the total payloads have reached 26, valid for building the Payload efficiency model. Table 4 shows the abbreviations of the used symbols.

Table 2. Sample data that was logged for six months, DT time, WL payload type, WH hours of work, SH hours of survey, TP of payload weight, SP survey weight, OPPH of ideal hourly loading weight

DT	WL	WH	SH	TP	SP	OPPH
05/07/2021		19	0			80
06/07/2021	Scrap	20	0	3,000	300	80
07/07/2021		20	8			80

Table 3. All collected data for six months after calculating the efficiency for each load

DT	WL	WH	SH	TP	SP	TPWS	WHWS	OPPH	OPTP	EFF%
05/07/2021	Scrap	59	8	3,000	300	2,700	51	80	4,080	66.18
09/07/2021	Phosphate	72	0	5,000	0	5,000	72	110	7,920	63.13
29/07/2021	Scrap	22	6	1,200	200	1,000	16	80	1,280	78.13
02/08/2021	Scrap	60	8	3,000	300	2,700	52	80	4,160	64.9
10/08/2021	Scrap	47	8	2,500	300	2,200	39	80	3,120	70.51

Table 4. Symbols

Symbols	Quantity
WL	Payload type
WH	Working hours
SH	Sweeping hours
TP	Payload weight
SP	Sweep weight
OPPH	Ideal hourly loading weight
TPWS	Payload weight without sweep
WHWS	Working hours without sweep
OPTP	Optimum payload weight
EFF	Efficiency

6.2. Experiment assumption

During the experimental work, the following assumptions have been made:

- Each load took more than one day to be loaded. We suppose to calculate the efficiency at the end of the day. But we waited until the full load was finished and we calculated the efficiency per payload.
- At the end of each payload, a scattered amount of the payload remained on the ship that could not be loaded directly. The sweep process must be carried out and assembled first before loading. As well as, it

took a different time from the daily loading. To simplify the design of the model, we subtracted it from the total weight of the payload and calculated the efficiency on the remaining quantity. In the future, we will take the time of the sweep into consideration and we will create an efficiency model for the sweep process.

6.3. Synthetic data generation

Businesses rely on data to create machine-learning models that can predict the future and enhance operational choices. Companies utilize synthetic data to construct models when historical data is unavailable or when the current data is insufficient due to poor quality or lack of diversity. The quality of synthetic data has been drastically improving, and its quantity makes up for deficiencies in quality. For instance, the majority of self-driving miles are accrued using synthetic data created in simulations. Pathare *et al.* [39], a comparison among the best synthetic data generator is conducted and evaluated by the users. In this paper, we build own model and generate its synthetic data as shown in Figure 7.

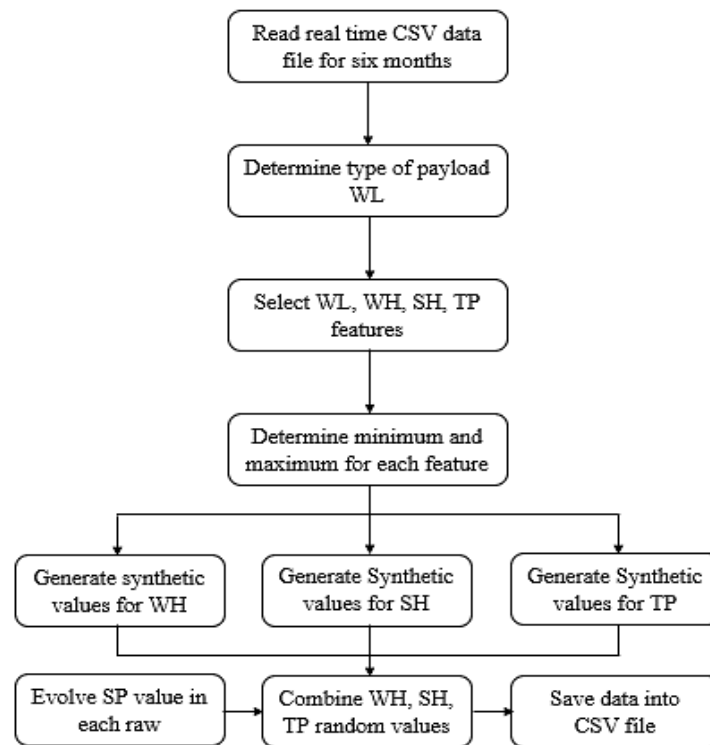


Figure 7. Synthetic data generation diagram

Recorded real time data for a period of six months was used to generate syntactic data, where around 15,000 samples of synthetic data were generated. As in Figure 7 minimum and maximum limit values for each feature WH, SH, TP were used to generate random values between maximum and minimum, and then generated values were combined together to generate synthetic data samples for each payload type. SP was fixed number for each payload type so it was involved with generated data each iteration, data samples were saved into CSV file. The generated samples can be divided into 1,763 scrap samples, 2,933 phosphate samples, 2,703 seed samples, 1,163 wheat samples, 500 beans samples, and 5,987 corn samples.

The model does not handle text data, so the payload type has been replaced with codes as in Table 5. We manually calculated the efficiency for all samples as we did before then efficiency column added to the synthetic data tables. About 15,049 synthetic data samples were generated, in order to verify this generated synthetic data, efficiency was manually calculated the for all samples as we did before in (9) and we removed all samples giving efficiency greater than 90% as it considered up normal values. Then efficiency column added to the synthetic data tables, Figure 8 represents a scattered distribution for features of generated synthetic with efficiency.

Table 5. Maximum and minimum values for WH, SH, TP, and SP features, this values used to generate synthetic values between minimum and maximum

WL	Code	Samples	WH (hours)	SH (hours)	TP (ton)	SP (ton)
Scrap	00	1,763	6-120	6-8	1,000-3,000	300
Phosphate	01	2,933	10-75	0	0	0
Seed	02	2,703	88-112	10	12,958-14,042	1,000
Wheat	03	1,163	117-154	10	18,078-18,430	1,000
Bean	04	500	30-47	5	1,963-1,985	300
Corn	05	5,987	99-135	10	12,424-13,387	1,000

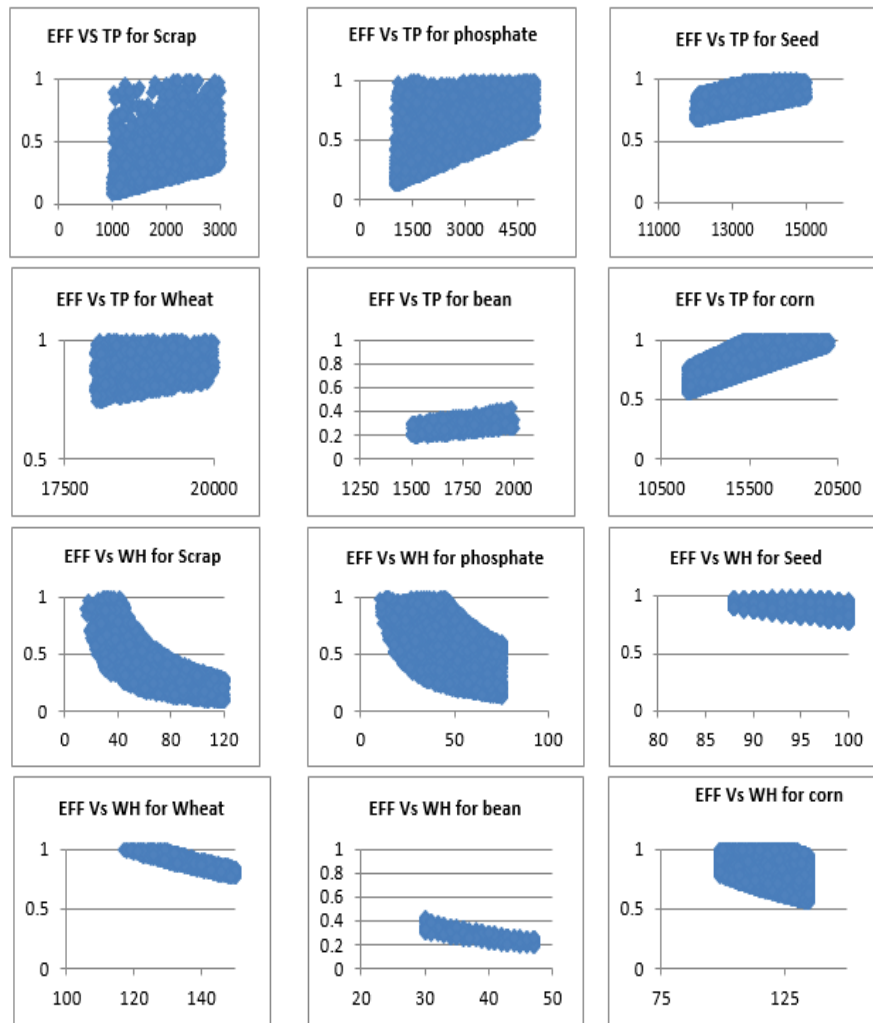


Figure 8. Scatter distributions (EFF-TP), (EFF-WH) for generated synthetic data different payloads, generated values lie between minimum and maximum values mentioned in Table 5 and no up normal values, and all of them can be considered linearly distributed

7. QC-GMHC EFFICIENCY PREDICTION MODEL

7.1. Training and validation data preparation

About 15,000 samples of synthetic data were prepared to train and validate the crane efficiency model. Training and validation data preparation block diagram is illustrated in Figure 9. The data was loaded, reviewed and displayed, each feature was fitted, transformed, and scaled to a given range, using simple estimator scales that translates each feature individually such that it is in the given range on the training set, e.g., between zero and one. Then features were selected which are WL, WH, SH, TP, SP. Features arrays split into random train and validate subsets using helper function, 20% (3,011 samples) of dataset used for validation and 80% (12,043 samples) of dataset for the training. Batches of training/validation temporal data generated using time series generator module.

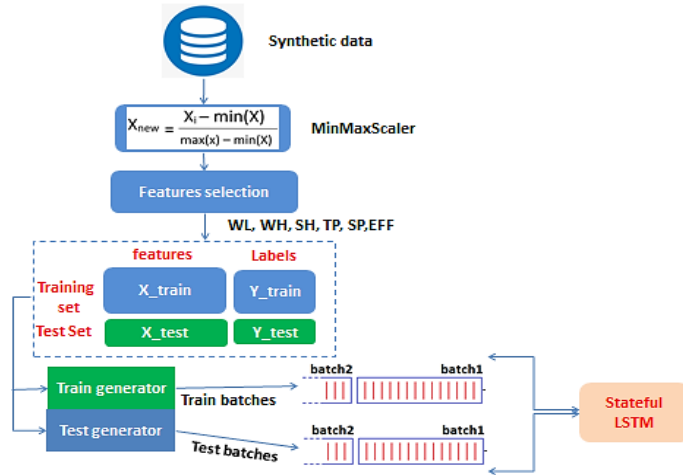


Figure 9. Data scaling and fitting features selection, training and test splitting, and training/test batches generation

7.2. Model training

A keras sequential model has been built to predict the efficiency of GMHC system as in Figure 10. A set of layers had been added to the model which can be summarized as: three LSTM layers, which use 128 batches of training/validation batch sets that had been produced in the data preparation stage; two LeakyReLU layers with a coefficient of alpha=0.5 and two dropout layers had been added between them. The model was fitted on data yielded batch by batch, after 50 epochs model was fitted with mean squared error: 4.3210e-4 and validation mean squared error: 0.0033.

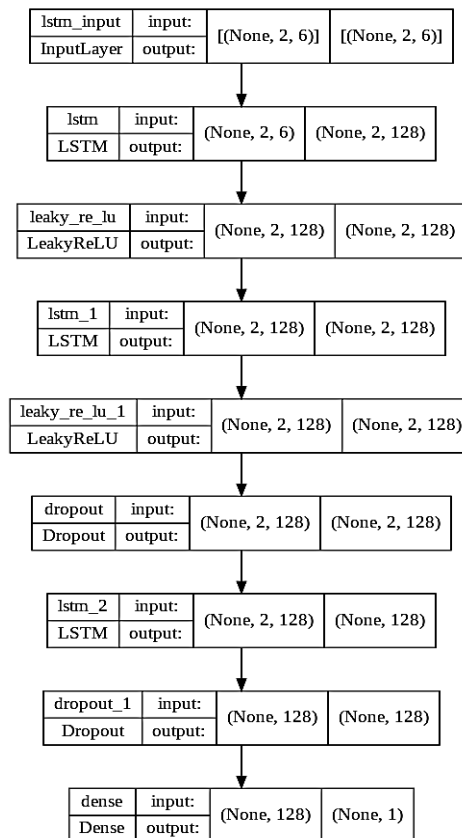


Figure 10. QC-GMHC DL model summery

7.3. Model validation

QC-GMHC prediction model has been tested and validated using 20% (3,011 samples) of data. Test generator function has been used to generate batches of validation dataset then an evaluation predictor was generated from evaluation batches using evaluate generator function to be compared with test result [40]. The X_test and Y_test dataset has been used with evaluation function in order to evaluate the model. The confusion matrix and accuracy have been calculated and represented as shown in Figure 11.

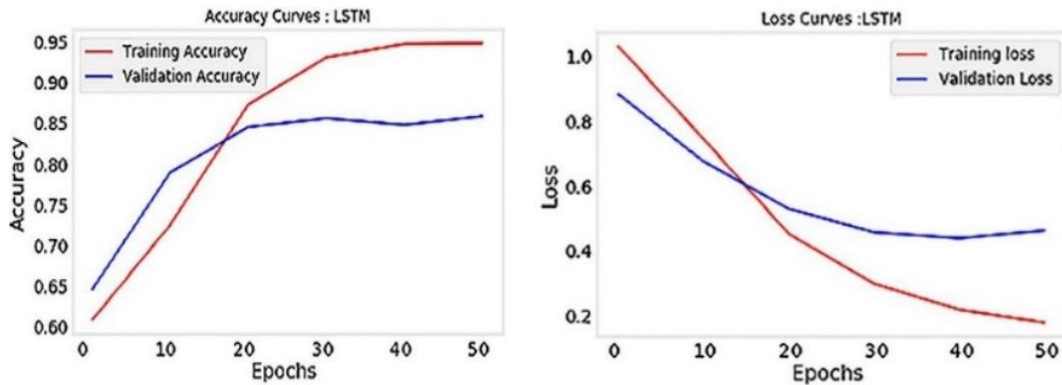


Figure 11. Accuracy and lose curves for QC-GMHC prediction curve

8. DISCUSSIONS

The absence of an indicator for the performance of the goods movable harbor crane leads to many problems, such as increased failure rate, high operating cost and increased fuel consumption. Therefore, this study introduced a system to improve the efficiency of the goods movable harbor crane called QC-GMHC. To read data from the PLC, serial communication was utilized to connect with the PLC using the OPC Sever program. The ESP-32’s Wi-Fi module receives data from the LabVIEW application via an Arduino mega that has been designed to do so. Data from the Arduino is sent to the IoT server via the ESP-32s Wi-Fi module, which is configured using the Arduino IDE software. Through this server, data was kept in order to monitor and operate the crane. The system components were installed in real time on GMHC in Damietta port, Egypt for a period of six months for collecting data. The output (efficiency measure) and the corresponding input features such as actual working hours, stopping hours, number of faults, rate of crane loads per ship, type of crane loads will help in making correct decisions that raise the production rate, improve maintenance quality and reduce the operating costs compared to working without this system. Now the system is not installed but SESCO TRANS Company accepted the system and started the procedures for installing it. Results of this study cannot be compared to others because this is the first research to present a smart QC-GMHC system.

8.1. Comparative result

A comparative result is shown in Table 6. The proposed methodology has achieved high performance compare to other scientific papers related to the same topic. The production rate has reached 30% in the proposed methodology with 3.5% increasing value than in [31].

Table 6. The comparative result

Study	Crane type	Control system	Cost-effective	Production rate	Efficiency
Lee <i>et al.</i> [31]	Tower crane	Wireless control video technology and RFID	---	26.5%	---
Gao <i>et al.</i> [32]	Swing angle measurement	A wireless microelectromechanical System devices and ZigBee wireless communication	---	---	---
Shi <i>et al.</i> [34]	Large-scale cranes	Narrow band IoT	---	---	---
Singh <i>et al.</i> [36]	Overhead crane	Two configurations for acquiring and transmitting data wirelessly to a remotely-located cloud server for analysis	---	---	---
The proposed system	GMHC	QC-GMHC	25%	30%	80%

9. CONCLUSION

QC-GMHC is proposed in this research using a prediction model that incorporates the IIoT. Taking into account factors like payload type, working hours, sweep hours, and total payload weight, the prediction model can estimate the GMHC efficiency of each ship. There are two components to QC-GMHC; the first is hardware, which was developed and tweaked for a full six months to ensure its optimal performance. Results from the data collection process revealed that no data had been missing for a period of six months. Part of the software was developed using models built from simulations of real data. The system was tried out and judged to be successful. Efficiency forecasting is within its capabilities. It was not a pleasant place to work, as we were subject to several limitations. Some limitations were addressed, but others, such as sweep efficiency, will need to be taken into account for further development. Cranes' failure rate, operating cost, and fuel consumption may all be reduced with the help of our proposed solution, which also increases their dependability and safety. The proposed solution has the potential to reduce the failure rate, operating cost, and fuel consumption of cranes. It can also increase the reliability and safety of cranes. Specifically, in future, we plan to: i) improve the sweep efficiency of the QC system; ii) develop a more robust hardware platform for the QC system; and iii) integrate the QC system with other logistics systems.




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