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IIoT-Enabled Digital Services for Maintenance Planning in Smart Production Logistics Using Maintenance Opportunity Window

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Abstract. Developing IIoT-enabled digital services is essential for facilitating human centered digital transformation and achieving resource-efficient production. IIoT-enabled digital services focus on providing the best possible value proposition to end users based on three main components including hardware, middleware, and visualization applications. An area of increasing interest is that of developing IIoT-enabled digital services in smart production logistics (SPL) that facilitate the delivery of material and information in manufacturing. Prior studies focusing on IIoT-enabled digital services give precedence to the location, energy consumption, and execution of material handling tasks in SPL. However, the literature neglects the importance of supporting staff responsible for maintenance of material handling equipment. Recent publications propose the use of Maintenance Opportunity Windows (MOW), yet this approach requires extensive calculations unsuitable to the dynamic environments of manufacturing. Addressing this need, the purpose of this study is to propose IIoT-enabled digital services for detecting MOW in material handling for the automotive industry. This study presents two contributions. Firstly, we draw extant knowledge about IIoT architectures in SPL to a novel context, namely that of MOW. Accordingly, this result reduces the time and resources for acquiring, processing, and identifying empty spots in MOW as compared to prior studies. Secondly, the study proposes IIoT-enabled digital services in material handling targeting maintenance staff including finding, filtering, and detecting the status of forklifts and their MOW. In doing so, the results complement existing literature about SPL targeting the autonomous coordination and scheduling of material handling. This is critical for offering digital services supporting the working needs of maintenance staff for a human centric industrial transformation.

Keywords. Smart Production Logistics, Material Handling, Maintenance Opportunity Window, Maintenance Planning

1. Introduction

Developing IIoT-enabled digital services is essential for facilitating human centered digital transformation and achieving resource-efficient production [1, 2]. IIoT-enabled

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digital services focus on providing the best possible value proposition to end users based on three main components including hardware, middleware, and visualization applications [3]. IIoT-enabled digital services include a novel proposition for building and maintaining a competitive advantage originating from the collaboration and sharing of information between machines and staff [4]. An area of increasing interest is that of developing IIoT-enabled digital services in production logistics that facilitate the delivery of material and information in manufacturing.

Prior studies focusing on IIoT-enabled digital services give precedence to the location, energy consumption, and execution of material handling tasks in production logistics [5]. An area of equal importance receiving scant attention is the maintenance of equipment in material handling [6, 7]. Two reasons motivate the need for IIoT-enabled digital services in this field. First, staff lacking IIoT-enabled digital services rely on ad hoc practices for scheduling, executing, and monitoring the maintenance of equipment in material handling. A situation that leads to increased cost, inefficient use of resources, and lost competitiveness [6]. Second, recent advances including the use of Maintenance Opportunity Windows (MOW) [8], applicable to maintenance of material handling, are difficult to apply because this require extensive calculations unsuitable to the dynamic environments of manufacturing [9]. Instead, developing IIoT-enabled digital services for maintenance in material handling presents critical benefits supporting human centered digital transformation. These benefits include continuous learning process, experimentation, testing and applying new processes, or experimenting with new ways of working under continuous change [10, 11].

Addressing this need, the purpose of this study is to propose IIoT-enabled digital services for detecting MOW for material handling equipment (MHE) in the automotive industry. We consider the case of the automotive industry because of its increasing need for MHE critical for delivering material on time and realizing flexible and convertible manufacturing systems at all stages of car production [12]. The study applies extant understanding about IIoT in Smart Production Logistics (SPL) and MOW, and proposes a model applying a real-time location system for forklifts executing material handling tasks indistinct of production systems or product types. The conceptual model describe three essential tasks for detecting MOW in material handling including information acquisition, processing and prediction.

Accordingly, the results of the study provide three contribution critical for achieving resource-efficient production in modern day factories. Firstly, we draw extant knowledge about IIoT architectures in SPL to a novel context, namely that of MOW. Accordingly, this result reduces the time and resources for acquiring, processing, and identifying empty spots in MOW as compared to prior studies. Secondly, the study proposes IIoT-enabled digital services in material handling targeting maintenance staff including finding, filtering, and detecting the status of forklifts and their MOW. In doing so, the results complement existing literature about SPL targeting the autonomous coordination and scheduling of material handling. This is critical for offering digital services supporting the working needs of maintenance staff for a human centric industrial transformation.

The remainder of this study is structured as follows. Section 1 presents related works. Section 2 describes the conceptual model. Section 3 proposes IIoT-enabled digital services. Section 4 discusses the implications of this study. Section 5 concludes this study.

2. Related works

2.1. Smart production logistics

SPL is a novel concept redefining the movement of materials and information within the physical boundaries of a factory. SPL refers to applying digital technologies for realizing the active perception, response, and autonomous decision making [13]. SPL facilitates the acquisition, handling and use of information in a variety of tasks including material handling, warehousing, inventories, packaging, order picking, and information management [14]. SPL is not the only term for describing the transformation represented by digital technologies in production logistics. The literature offers alternatives including logistics 4.0 [14], or smart logistics [15]. We apply the term SPL instead of logistics 4.0 to distinguish from the national German initiative associated to Industry 4.0. Likewise, we adopt the term SPL instead of smart logistics to distinguish from the movement of material inside a factory as opposed to the larger supply chain context.

IIoT is a critical component of SPL, and its importance underscored in extant literature [16, 17]. The use of IIoT in SPL enables the visibility of materials and information and reduction of errors [18]. IIoT refers to the connection between all industrial assets including machines, control and information systems, and processes [19]. Accordingly, resources in production logistics including IIoT devices can generate data, and share information and interact with their environment [20]. Prior studies present diverse IIoT devices in SPL including radio frequency identification devices (RFID), robots, cameras, or AGVs [21]. The literature indicates that RFID are decisive because of their effortless installation on MHE (e.g. conveyors, AGVs, forklifts, robots, tugger trains, or vertical storage systems).

An essential aspect for realizing the benefits of SPL includes the development of an IIoT architecture facilitating the acquisition, processing, and identification of information [22]. The literature includes alternative architecture for IIoT including The International Telecommunication Union supports an IoT architecture, and The Reference Architectural Model Industrie 4.0 (RAMI 4.0) [19]. This study applies a three-layered including a physical, cyber and virtual layers [23]. This choice is informed because of its widespread use in SPL [13, 16, 24]. The physical layer consists of sensors, actuators and controllers interconnected to a local area network capable for sending and receiving real-time data. The cyber layer facilitates the acquisition, processing, and identification of information. The service layer contains generic and application specific functions accessed remotely.

2.2. Industrial internet of things enabled digital services

IIoT is indispensable for achieving digital services leading to increased manufacturing competitiveness. Digital services (DS) includes the deployment of digital technologies to support the transformation from a product-centric to a service-centric business model [25]. DS refer to dynamic value co-creation configurations of resources, including people, organizations, shared information (language, laws, measures, methods), and technology, all connected internally and externally to other service systems by value propositions [26]. Accordingly, IIoT connects all the industrial assets, including machines and control systems, with the information systems and the business processes [19].

Recent studies identify four capabilities for realizing IIoT enabled DS including monitoring, control, optimization, and autonomy [2]. Monitoring refers to real-time information reporting on the location and condition of resources [27]. Control involves corrective actions and response to events or changing conditions facilitated by software and actuated by smart products [4]. Optimization constitutes applying algorithms and analytics to real-time and historical information for improving the performance of a manufacturing system [27]. Autonomy integrates the monitoring, control and optimization capabilities facilitating the operation of equipment, or coordination and response to information independent of human interaction [28].

A number of studies exemplify the use of IIoT-enabled digital services in SPL. For example, Flores-García et al. [29] propose a framework applying machine learning and developing digital services for the dynamic scheduling and execution of material handling tasks in SPL. Jovanovic et al. [30] describe the use of machine learning and analytis for realzing proactive monitoring in spare part logistics. This contributes with data insights from all active and connected machines. Guo et al. [24] propose IIoT enabled DS for SPL enhancing the capability of intelligence, flexibility, and resilience leading to reductions in waiting time, makespan, and energy consumption. Kim at al. [31] analyze the use of digital twins in SPL and digital services including monitoring, prescription and prediction for material handling enhancing economic, environmental, and social sustainability.

2.3. Maintenance opportunity window

Maintenance operations have a direct relation with the manufacturing performance of production systems. Generally, maintenance tasks are planned and prioritized based on heuristics or experience based [32]. In order to tackle this, opportunistic maintenance policies must be sought. [33] first introduced the concept of "Maintenance Opportunity Window" using the utilization of buffer contents. The opportunity windows provide naturally occurring opportunities of window within scheduled production, during which maintenance tasks can be performed. MOW method incorporates real-time information about production and maintenance failure conditions [34]. There are two types of MOW, passive and active. A passive MOW occurs when the machine is starved or blocked due to the occurrence of random failures on its upstream or downstream machines [8]. An active MOW for a machine is when the machine can be strategically shut down for maintenance during its production time if the short-term system production requirement can be satisfied by utilizing the inventories in the machine's downstream buffers [8]. When it comes to short-term maintenance tasks allocation for machines, these passive and active MOWs can be used. The existence of buffers plays an vital role in developing these short-term policies [34].

The stoppage of the slowest machine will result in the production loss of the entire system, i.e. the bottleneck machine in the system. However, a stoppage in a non-bottleneck machine can also make the bottleneck machine go idle or starved eventually. Hence, [8] proposes identification of critical downtime of each machine. The critical downtime is defined as the maximum time a machine can go down without making the bottleneck machine go idle or starved. Such information from real-time data from machines can help in identifying the passive MOWs in each machine. These type of short-term policies are extremely useful for executing maintenance activities on machines. This effective maintenance schedules help in avoiding unnecessary stops in production time for maintenance intervention thereby leading to increased system productivity. MHE are also important elements of production system and a critical MHE will impede system productivity [7]. These equipment can also fail and need preventive and reactive maintenance interventions. Applying this same logic of MOWs for machines to MHE should also be possible using real-time data. Therefore in this paper, we explore the possibilities of passive MOWs for MHE using real-time data.

2.4. Maintenance of material handling equipment in smart production logistics

Extant literature on SPL focuses on the improving the cost, quality and time related to the movement of materials and information [14]. Despite the importance of SPL for acquiring, handling, and using information originating from MHE literature on the use of this data for maintenance purpose remains scarce. To the best of our knowledge only a handful of publications address maintenance for MHE in SPL. For example, [35] propose a novel cross-layer data gathering approach that collects the industrial big data from various resources and transmits to the control center in the real-time for active monitoring and maintenance in the automotive industry [36] discuss an application of the IIoT in bulk solid handling and transportation systems and the utilization of big data for addressing down-time and unexpected maintenance. [37] describe a proactive approach to smart maintenance and logistics as a auxiliary and service processes in a company, and study the case of laser guided AGVs, automated storage and retrieval systems, and conveyor systems.

3. Conceptual model for detecting maintanance opportunity windows

SPL is a novel concept and there are many studies about SPL architecture and application. However, we were not able to find any literature that combines the MOW concept with SPL. Therefore, we are suggesting a conceptual model based on SPL architecture including the services for detecting MOW with IIoT. The components of the conceptual model originate from extant knowledge on SPL present in the related works including an architecture involving physical, cyber, and service layers.

The physical layer comprehends material handling resources and IIoT devices. The purpose of the physical layer is that of executing tasks, and generating and transmitting real-time data during material handling. Material handling resources include conveyors, AGVs, forklifts, robots, tugger trains, or vertical storage systems. IIoT devices comprehend cameras, ultrawide bandwith (UWB) tags, or radio frequency identifiers (RFIDs) sense points.

The cyber layer establishes the communication of information for detecting and realizing digital services based on IIoT for MOW in material handling. A first aspect of the cyber layer includes acquiring, processing, and identifying information originating from resources in material handling. During information acquisition, the cyber layer obtains data including the name, time stamp, status (e.g. use, idle, or stop), and the location of resources. Then, the cyber layer transforms data into information by recording, organizing, and retrieving, and trasferring information. Finally, the cyber layer identifies information including the passive opportunity windows of resources in material handling, bottle necks, and the time that a resource may be idle without affecting a production logistics system. A second aspect of the cyber layer involves finding, filtering, and assigning information about MOW. Finding refers to the search of maintenance tasks in a database and their order of precedence. Filtering consists of the pairing between the time of passive opportunity windows of resources in material handling and that of maintenance tasks. Assigning involves defining a maintenance task for a particular passive opportunity windows.

The service layer consists of four IIoT-enabled digital services providing insight to staff about MOW in material handling. The purpose of the service layer is facilitating decisions for staff related to MOW of resources in material handling. The IIoT-enabled digital services include a monitoring, control, optimization, and autonomous decision services. Figure 1 presents the proposed conceptual model including IIoT-enabled digital services in material handling for detecting MOW.

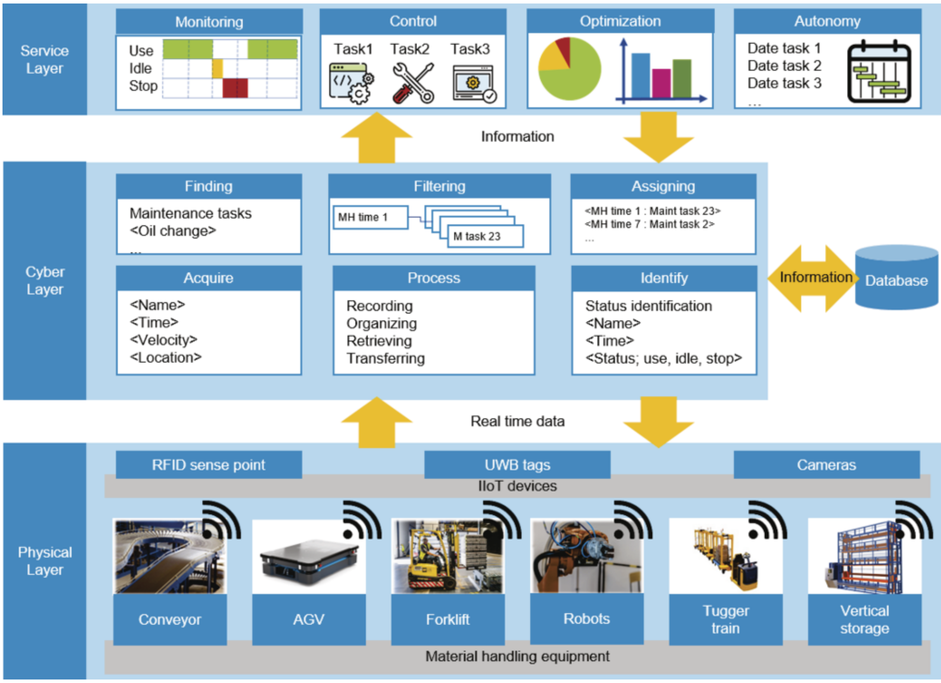

Figure 1. presents the proposed conceptual model including industrial internet of things-enabled digital services in material handling for detecting maintenance opportunity windows

This conceptual model can be used to detect the MOW of material handling equipment. For example, AGV needs to be charged based on the charging strategy. This strategy can have minimum battery level or how and where to find the right charging stations. Battery level and energy consumption can be measured by the sensor which is already installed in AGV and this data can be transferred in real-time to the cyber layer and processed to detect the MOW. The main purpose of finding the MOW of AGV regarding the charging policy is not to block the logistics flow and minimize unnecessary movement of the AGV.

4. IIoT-enabled digital services

As we mentioned in the previous section, the proposed conceptual model (Figure 1) aims to provide IIoT-enabled digital services to users. This section introduces monitoring, control, optimization, and autonomy digital services with some examples. Figure 2 represents a brief summary of these services.

The first step of IIoT-enabled services starts from the monitoring service using real-time data. Although the conceptual model mainly proposed in this study aims to detect MOW, real-time data collection of production logistics facilities is essential to achieve this goal. MOW can be detected by analyzing the operating pattern of the facilities. The data collected from the physical layer is processed and identified in the cyber layer, and provide users data to monitor real-time location or the status of the logistics facilities. The state of the facilities can be defined as the use, idle, or stop. In addition, predefined KPIs can be visualized based on the collected data to provide uses with information such as the utilization of logistics facilities, total traveled distance, total idle time, and so on.

As a next step, it is possible to provide a service to control logistics facilities based on the data collected from the monitoring service. By analyzing the operation historical records, the operation zone for each logistics facility can be adjusted or the route can be changed for better efficiency. In addition, predefined maintenance activities can be assigned to the identified MOWs based on the monitoring results. Although there may be differences depending on the type of logistics facilities, maintenance tasks such as battery charging, oil change can be assigned in consideration of the length of the identified MOW.

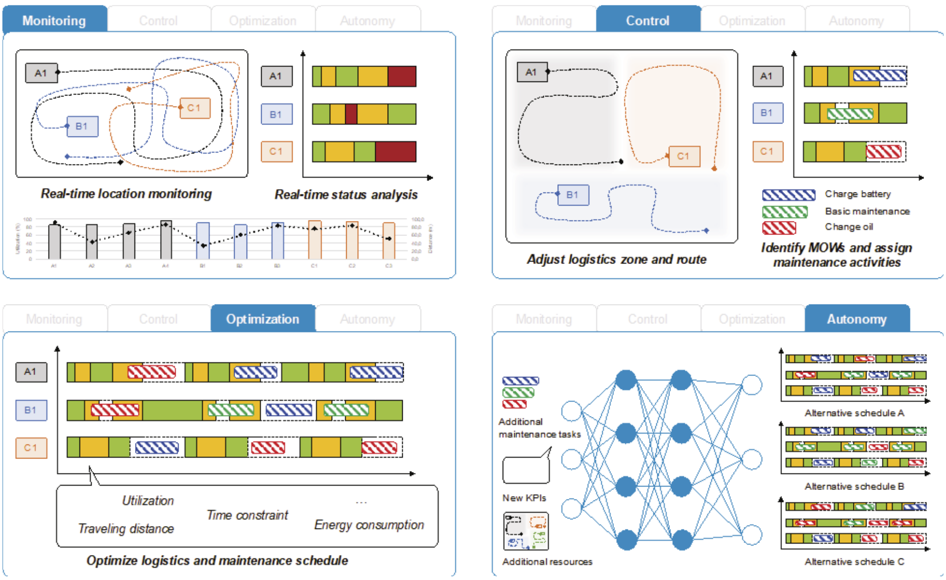

Figure 2. presents the IIoT-enabled services (monitoring, control, optimizaiton and automomy)

In our conceptual model, optimization service refers to a service that derives an optimal schedule in consideration of utility, time constraints, energy consumption, traveling distance when we allocate the maintenance activities to the MOWs. The most important thing in this service is to comply with the time constraint so as not to disturb the main flow of the production system, which is a very important factor in achieving the planned throughput of the production system.

With the development of computing power and advanced algorithms, various artificial intelligence (AI) technologies have been developed and are being used in various fields. The proposed autonomy services in this study use AI technologies to help optimization respond to various situations as well as limited situations. For example, even when new maintenance tasks, facilities, or KPIs are introduced, the AI-trained model can be used to generate multiple schedule alternatives and provide users with information about which alternatives produce better results in the current situation or in the near future.

5. Discussion

This study provides insight for managers responsible for planning and execution of preventive maintenance tasks for MHEs without its force shutdown. A conceptual model is proposed exemplified using a case in the automotive industry.

Currently, the passive MOW predictions are proposed for industrial machinery operating in production systems [8]. The analytical models proposed include data from the machines, such as machine states, downtimes, cycle times, downstream and upstream buffer data [8]. Whereas, in this paper we propose MOW for MHEs. MHEs play a vital part in the production system. Likewise machines, disturbances to MHEs cause reduction of production throughput. In our conceptual model, we use data from the MHEs for the MOW prediction, such as MHE schedules, path, downtimes, and total number of MHEs in the systems as well as redundancies, if available. As a conceptual model, we assume the availability and quality of these data in industrial setting. Furthermore, we propose the linkage between the physical, cyber and service layers. All these together will function as an IIoT enabled digital service to the manufacturing company enabling integrated decision-making.

An integrated decision-making process is required for MHE, including the maintenance function [9]. Often the maintenance function is neglected in MHE planning as compared of other machines and equipment in the production system. In this paper, we proposed an integrated scheduling approach for MHE using passive MOW identification using real-time data. A key expected result of our proposed approach is utilizing the real-time data (i.e. production schedules). Using this data the active and inactive states of the MHE can be identified. The inactive state of the MHE is the passive MOW, where preventive maintenance tasks of the MHE can be performed without forced stop [8]. Depending on the length of the MOW that each MHE has short-term preventive maintenance activities can be planned. The main utility of these MOWs is that these preventive tasks will be executed during the production hours, i.e. forced shut down on production for performing preventive maintenance activities can be avoided as well as investing in multiple MHEs for redundancy can also be avoided. This will directly lead towards increased production throughput, optimal number of MHE resources as well as its maximized utilization.

Optimizing the quantity of MHE is necessary to achieve highest productivity with lowest cost possible [7]. Poor maintenance planning or the lack of maintenance is a key aspect of low efficiency of MHE. Due to this problem, manufacturing companies may plan for redundancy and invest in extra MHE: With our proposed model, we can help the manufacturing companies to use an optimized number of MHE to fulfill the production tasks. We propose maintenance opportunity windows for identifying naturally occurring times in the production schedule to plan and execute MHE maintenance activities.

Based on the proposed model, another expected future opportunity is integrating the maintenance plans with the production logistics scheduling system. This approach calls for synergy between the production logistics and maintenance schedules. In addition, it requires sharing of data between the two organizations. A joint planning system also enables the different organizations in the company to focus on the overall goals, i.e. increasing productivity, increasing efficiency, reduction of costs, etc.

6. Conclusions

This study proposed IIoT-enabled digital services for detecting maintenance opportunity windows (MOW) in material handling for the automotive industry. The study presented two contributions. First, we provides a novel architecture including IIoT-enabled digital services for MOW in material handling. Second, the study proposed four IIoT-enabled digital services including monitoring, control, optimization and autonomous decisions.

This study include three limitations. A first limitation of this study includes its conceptual nature. Accordingly, future research could involve testing the proposed architecture in a laboratory environmenta, and assessing its operational benefits. A second limitation involves a focus on the automotive industry. Therefore, there exists the need to verify the suggestions of this study to the idyosincracies of material handling in additional industries. A third limitation concerns the need for the selection of an algorithm that efficiently assigns maintenance tasks to material handling passive opportunity windows. Future studies could investigate the use of machine learning for addressing this limitation.

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