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Enhancing smart shop floor management with ubiquitous augmented reality

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This paper describes a framework for implementing Smart manufacturing Shop floor systems based on the Ubiquitous Augmented Reality technology (SSUAR). The proposed system makes use of data sharing between shop floor resources and a sensor network in order to optimise the production schedules for carrying out projects. The optimisation is performed in real-time and the production scheduling responds to new projects as well as the changing status of resources, such as machines and workers. Ubiquitous augmented reality interface has been developed and utilised as a user interface for the shop floor workers to receive information, instructions and guidance from the experts and manufacturing systems, and to update the systems on task parameters, such as estimated completion times, progress and machine status. A review of related work, methodology and implementation of the proposed system, and a case study are presented in this paper. Using this architecture, real-time scheduling of tasks in the smart shop floor can be achieved. The case study demonstrated the ability of SSUAR to integrate task scheduling with two-way communication between the system and the users.

Keywords: shop floor; task scheduling; ubiquitous computing; internet of things; augmented reality

1. Introduction

The competitive and fast-growing market of modern manufacturing has led to multi-variety and small-batch production processes, i.e. agile and responsive to the consumers' demands, especially for manufacturing shop floors (Thoben, Wiesner, and Wuest 2017). These manufacturing processes are generally complex and highly customised, and the accompanying on-site manufacturing data and information are massive and diverse. In the past five years, IoT (Internet of Things) technology has been developed and implemented to store, capture, transmit, and process on-site and/or off-site manufacturing data (Cao et al. 2017). IoT has been integrated with manufacturing management systems, such as manufacturing execution systems (Zhong et al. 2013), product lifecycle management (Stark 2015), enterprise resource planning (Chofreh et al. 2014), etc. The integration has brought creative strategies and models for shop floor production management, e.g. cyber-physical manufacturing systems, cloud manufacturing systems (Cao et al. 2017; Theorin et al. 2017; Zhang et al. 2014), automating the coordination and adoption of manufacturing services and resources. However, many manufacturing activities need to involve human efforts, e.g. pre-manufacturing activities (production planning, task scheduling), manufacturing activities (machine operation, maintenance), etc. In order to support the human participants in these activities, multi services are required to be integrated to the shop floor production management systems, e.g. production planning service, production scheduling service, operation guidance service, etc.

Augmented reality (AR) can provide a seamless interface that bridges the gap between the real and virtual world, so that the connections between users and the smart environment can be enhanced (Mourtzis, Vlachou, Zogopoulos, and Fotini 2017). A large number of successful AR systems have been rolled out to consumers, e.g. Hololens, Lowe's targets store AR navigation, etc. Recent development of IoT enables the extension of conventional AR applications to ubiquitous augmented reality (UAR) (Grubert et al. 2017). Compared with conventional AR technology, UAR can be seen as a context-aware, responsive, and continuous AR experience, where the users can interact with the always-accessible and appropriate computation resources at any moment and at any place (Lin et al. 2017).

The use of UAR to achieve smart manufacturing and performance measurement has constituted a critical step in the industry (Yew, Ong, and Nee 2016; Wang et al. 2016). Therefore, it is meaningful and of great significance to develop UAR-enhanced smart shop floor management systems to improve the productivity, robustness, and efficiency of the manufacturing shop floor. The implementation of UAR comprises a wide application of industrial IoT systems, such as RFID tags and readers, sensors, actuators and mobile computing devices (e.g. head-mounted display (HMD), tablets, etc.), to provide a

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ubiquitous human-machine interaction scheme so that the users can interact with the smart shop floor at anywhere and anytime. However, research on UAR-enhanced smart shop floors is still in the exploratory and prototyping stages (Yew, Ong, and Nee 2016).

This paper presents a new paradigm of Smart manufacturing Shop floor systems based on the UAR technology (SSUAR). A comprehensive architecture of the system is proposed, where multiple services can be provided for both on-site users (e.g. machine operators) and off-site management users (e.g. process planners). Using this architecture, real-time scheduling of tasks in the smart shop floor can be achieved. To handle the dynamic characteristics of task scheduling, a shop floor task scheduling algorithm that integrates real-time data captured from the smart shop floor sensors as well as inputs by UAR interface is proposed. The disturbances and exceptions (e.g. unplanned machine failures, material shortages, etc.) can be captured and resolved in a timely manner based on the UAR interface. The production guidance system receives the production schedule and guidance information from the production management system, and releases instructions to the terminals attached to each station (e.g. small single-board computers attached to the machines). The SSUAR system monitors the production activities by collecting information of the production status and changes and coordinating production processes according to the production schedule. When there is deviation between the actual progress and the production schedule, the system will remind the process planners by the UAR interface to revise and update the task schedule.

This paper begins with a review of the state-of-the-art UAR and smart shop floor systems (Section 2) and an overview of the proposed system (Section 3). A description of the workflow and functional modules of SSUAR is given in Section 4. A prototype implementation of the system and case study are presented in Section 5, and Section 6 summarises the study and recommends the future work.

2. Related works

2.1. *Smart shop floor*

The implementation of smart factories and shop floors is an active research topic aimed at making use of the technologies of the digital age to enhance the productivity, flexibility and ergonomics of manufacturing systems (Mourtzis, Vlachou, Zogopoulos, and Fotini 2017). Cutting edge technologies and concepts, such as cyber-physical systems (CPSs) where physical processes are monitored using sensor networks and controlled by computers, have been employed in numerous smart factory researches. Bergweiler et al. (2015) described a framework for a self-monitoring CPS that monitors and verifies the manufacturing processes of individual workpieces, and outputs monitoring data on a variety of mobile devices. Zhang et al. (2011) implemented a real-time shop floor production monitoring and scheduling system using RFID-based object tracking and cloud-based data services. Tang et al. (2016) presented a smart shop floor architecture that performs scheduling of operations through agents that control the resources in the shop floor. Kolberg, Knobloch, and Zühlke (2017) have discussed ways of using information sharing and intelligent manufacturing resources to set up production lines according to lean production guidelines. Other functions of a smart shop floor and/or factory that have been studied through the application of digital technologies include mass customisation (Mourtzis, Doukas, and Psarommatis 2013), service-oriented industrial applications (Schuh et al. 2014; Herterich, Uebernickel, and Brenner 2015) and skills transfer (Bleser et al. 2015). However, more state-of-the-art interaction methods need to be considered in these systems.

Job scheduling in a factory shop floor has been studied since the 1970s. However, in recent times, real-time resource and personnel tracking technologies have added another dimension of dynamically changing shop floor conditions to the scheduling problem. Marichelvam, Prabaharan, and Yang (2014) proposed a discrete firefly algorithm to solve the hybrid flow shop scheduling problems to optimise the makespan and mean flow time of a shop floor. Wang et al. (2016) made use of real-time data from a shop floor to plan the job and machine sequences in a scenario with multiple jobs and multiple machines. Leng and Jiang (2017) proposed a dynamic scheduling approach by considering the elements of discrete manufacturing system (e.g. parts, manufacturing activities, and equipment) and the relationships among them to solve the multi-resources problem. More recent job scheduling studies have been reported by Gao et al. 2018; Ruiz-Torres et al. 2018; and Matta 2018. In order to improve current job scheduling systems, it is necessary to monitor the production operation in the smart shop floor and modify the production plan in real time.

2.2. *UAR in manufacturing*

With the development of portable viewing devices with powerful processing and graphical rendering hardware, such as tablets, smartphones and HMDs, AR has great potential as an intuitive user interface for displaying information and interacting with machines and services in smart factories and shop floors (Varela et al. 2016). An AR system for operator support in human-robot collaborative assembly was proposed (Makris et al. 2016; Michalos et al. 2016). Quint et al. (2016) demonstrated a system for assisting industrial workers in carrying out manual tasks using AR visualisation devices. Mourtzis, Vlachou, and Zogopoulos (2017) proposed a cloud-based platform for condition-based preventive maintenance, supported by a shop-floor monitoring service and an AR application. Yew, Ong, and Nee (2016) described a UAR manufacturing system that improves different user perception of the information in a manufacturing facility and enhances their interaction with manufacturing software in order to meet the rapidly changing demand and mass customisation. The status of operations in the smart shop floor captured using the ubiquitous devices (smart sensors and terminals) is necessary to improve the productivity and efficiency of the activities in the smart shop floor.

3. Overview of SSUAR

Figure 1 illustrates the proposed SSUAR, which is a smart shop floor management system enhanced with ubiquitous AR. SSUAR can provide real-time information-driven support and management of shop floor activities through ubiquitous interaction between shop floor workers, manufacturing resources and management. SSUAR can monitor the production operation in the smart shop floor and modify the production plan in real time taking into consideration the operation information captured by the ubiquitous devices (smart sensors and terminals), in order to improve the productivity and efficiency of the activities in the smart shop floor. This is achieved through real-time monitoring of the production processes, dynamic task schedule optimisation, and displaying AR operation guidance to the shop floor workers according to the task progress and worker location. SSUAR consists of three modules, namely, the smart shop floor (SS) module, UAR functions (UARF) module, and cloud services (CS) module (Figure 1).

4. Workflow of SSUAR and cloud services

4.1. Description of workflow

Figure 2 shows the workflow of SSUAR. The production planners design and plan a production schedule based on the orders received; they are supported by the cloud services of the production planning service (PPS) and dynamic tasks scheduling (DTS). The operation guidance service (OGS) extracts task information from the production schedule, and translates the schedule into operation guidance for on-site users (e.g. machine operators, engineers, etc.). Next, the system delivers the operation guidance to the terminals embedded in or attached to the respective manufacturing resources via WIFI and collects the production status information captured from the smart sensors. The guidance for each task is displayed as AR contents for the on-site operators. SSUAR is enabled to capture and process a large amount of production status data and infer implicit context information to support the on-site users' operation (timely operation guidance) and management users' decision making (whether to modify and/or re-schedule the production plan).

There are two shop floor conditions that can lead to the need to re-schedule the production process. The first condition occurs when new projects and jobs have been received, and the production processes need to be rescheduled to achieve optimal productivity and efficiency. The second condition is due to real-time events in the shop floor. When an exception occurs (e.g. machines breakdown), the shop floor supervisor/operator can input the cause and effect to SSUAR via AR ubiquitous interaction devices on-site so that the production planners can re-schedule the local manufacturing tasks on certain machines to reduce the influence of the exception to the overall makespan of the projects. Therefore, the system can assist the production planners to adjust the production plan dynamically and timely according to the status of the production operations. The guidance information will be displayed as AR content to the on-site users based on task progress and the real-time location of the users. This cycle will be continuous.

4.2. Smart shop floor (SS) module

The SS module comprises manufacturing resources (e.g. CNC machines, assembly workbenches, etc.), ubiquitous devices (e.g. smart sensors, interaction devices, distributed computing resources, etc.), and the on-site users. The ubiquitous devices can be divided into three major categories, which are smart sensors attached to or embedded in the manufacturing resources (e.g. terminal computers, RFID tag/reader, etc.), human motion capturing devices (e.g. infrared tracking), and the ubiquitous interaction devices (e.g. HMD/tablet). The manufacturing tasks are handled by the SS module, i.e. the manufacturing task workspace for the users. In the proposed smart shop floor, the ubiquitous devices are configured to be controlled and managed by terminals and/or processors distributed and located in the shop floor, and these terminals/processors are connected by a local network to form the manufacturing IoT. Each terminal/processor serves as a control node of the smart shop floor, i.e. the ubiquitous computation resources for on-site users. Supported by the UARF module, on-site users can interact with

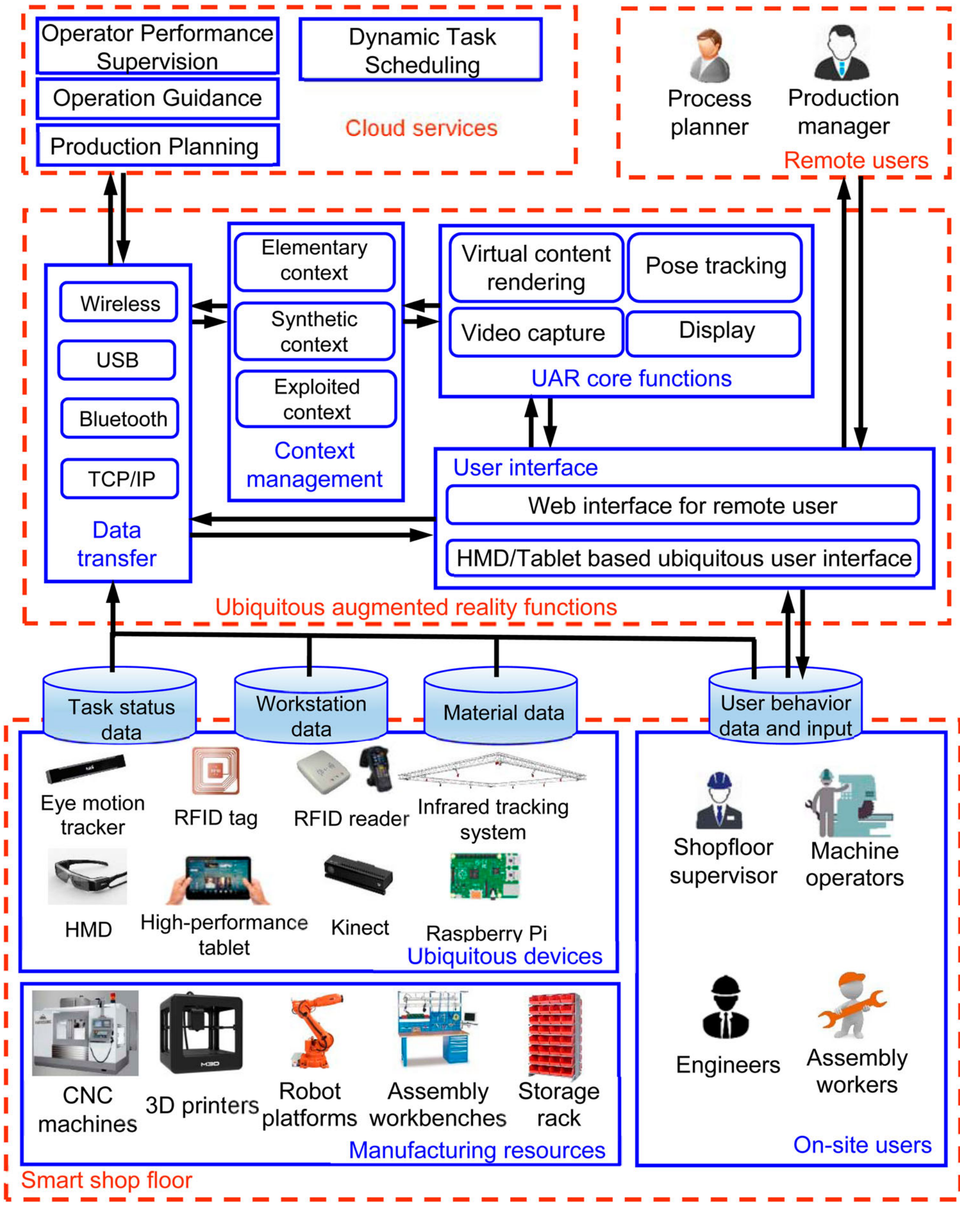


Figure 1. Architecture of SSUAR.

any of the control node, exchange information, and obtain the computation services ubiquitously, i.e. at any location and any time in the smart manufacturing shop floor environment. A server computer is implemented to provide the cloud services.

4.3. UARF module

The UARF module comprises the core UAR functions, user interfaces (UI), and data transfer (DT) functions. The interaction options for the manufacturing resources and services can be presented either via AR interfaces or through more traditional screen-based 2D graphical user interfaces, depending on the suitability of these options. In the SS module, which is supported by the UARF module, operation/maintenance guidance and task schedule are shown as augmented contents using the ubiquitous UI to support the on-site users.

The scene of the smart shop floor with augmented contents is displayed to the on-site users via the UARF module, which consists of four core functions, namely, video capture, user tracking, display and user interaction. The video capture function captures the real smart shop floor scene using a camera embedded in a HMD/tablet, and receives tracking results of the poses of manufacturing resources (machines, materials, etc.) and/or on-site users in the smart shop floor in real time.

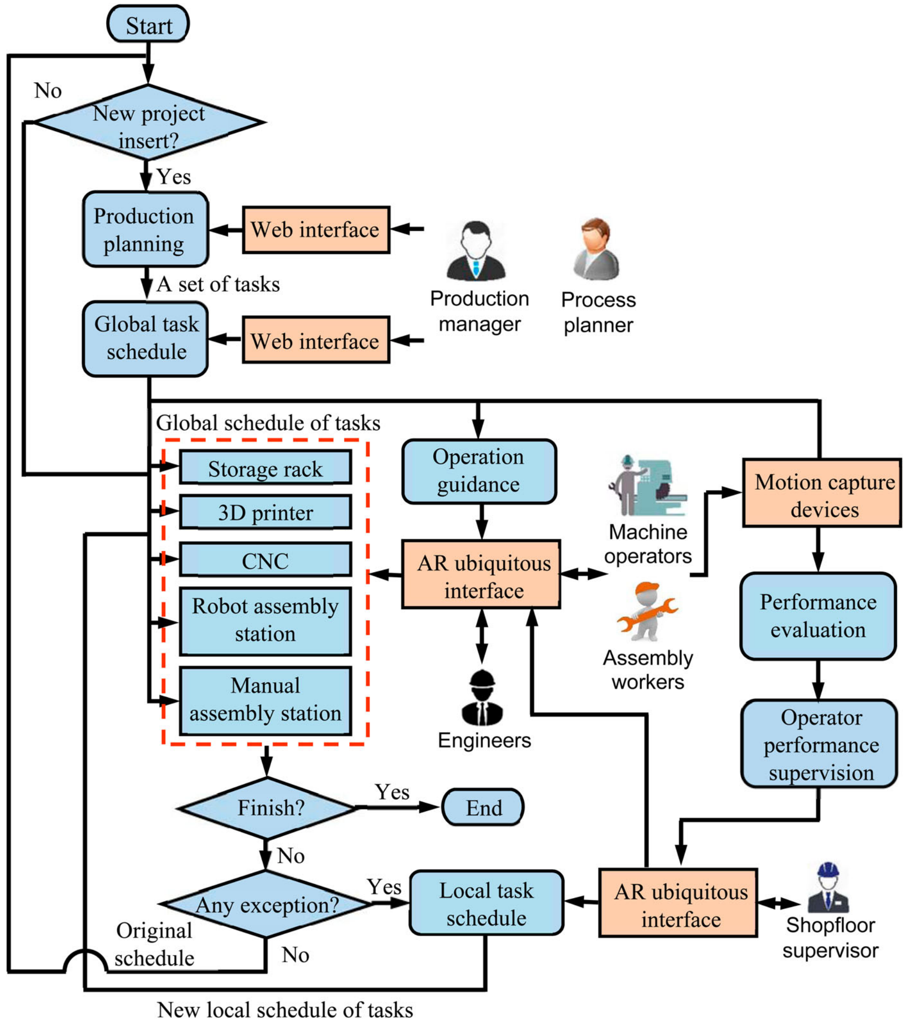


Figure 2. Workflow of SSUAR.

The tracking function determines the device or user position in six degrees of freedom, which is required for registration of the augmented contents.

User tracking serves three purposes, namely, to display AR user interfaces correctly to the users, to allow the cloud services to provide context-aware information to the users, and to trigger relevant AR guidance to users who are working with certain manufacturing resources in accordance with the production schedule. Pose tracking can be performed using sensors embedded in the environment, sensors that are attached to the users, or a combination of these techniques. While marker tracking, natural features tracking and motion capture technology have been employed in AR, viewing devices that are designed for indoor positioning, such as the Lenovo Phab 2 Pro and Microsoft Hololens, have recently become available to enable portable and robust AR systems at a low cost and without significant environment preparation. For cloud services, information about the users, such as their position in the environment, focus and intent, are useful in providing context-aware AR interfaces. Sensor fusion would be required to combine data from sensors, such as cameras, accelerometers and gyroscopes and other contextual cues, such as the time of day, historical behaviour of the users, etc.

Based on the pose tracking results, the scene (e.g. 3D models and camera images representing the physical world) is composed in the rendering component and rendered to the users. Finally, the users are allowed to interact with the physical and digital information using the UAR user interface. The implementation of recent affordable HMDs/tablets provides always-on access to information, and the users can interact with the SSUAR system when walking around the smart shop floor without interrupting the continuity of the immersive experience. In this research, two types of ubiquitous interaction devices, namely, HMD and tablet, are adopted to provide a natural way of human computer interaction in the SSUAR, and web interfaces.

Table 1. Data structures maintained in the cloud database of SSUAR.

Workers	Resources	Projects	Tasks
Name	ID	ID	Description
ID	Type	Tasks	Worker type required
Type	Location		Resource type required
Location	Tasks		Raw materials required
Tasks	Status		Estimated processing time
Status			

4.4. Cloud services

The CS module is a pool of services provided by the SSUAR system, namely, DTS module, OGS module, and the PPS module. The data are transferred among the CS module, SS module, and UARF module by the DT functions. These services make use of data monitoring in the shop floor as well as ubiquitous user interfaces for two-way communication between users and the services. The DTS module performs task sequence optimisation taking into account the dynamic conditions of the resources and workers, and re-scheduling on the fly when necessary. The PPS module captures the data related to project management and assigns tasks to shop floor that will be scheduled by the DTS module. A web interface is provided that allows off-site personnel, namely production planners and managers, to assign jobs to the shop floor and set parameters, such as project priority, due date and allocated time for the tasks. The PPS module also assigns dynamic machine maintenance and repair tasks when necessary, and provides an AR interfaces for on-site workers to report problems and downtimes of the machines. The OGS module generates information and AR aids for performing tasks that have been allocated to individual workers and displays them through the HMD or tablet. The graphical aids are registered to physical objects and locations in the shop floor so that workers can easily associate task instructions to the relevant machines and other resources in the shop floor.

4.4.1. Operation guidance generation

Four data structures, namely, workers, resources, projects and tasks, are defined and maintained in the cloud database and stored in the server, as shown in Table 1. These data structures are necessary to define the operation guidance templates and enable the intelligent inference of timely and appropriate guidance to the on-site users. Data are collected from on-site users and shop floor resources via the ubiquitous devices from each control node, and transferred to and stored in a cloud database in order to facilitate the functions of SSUAR.

The locations of workers are tracked either via user-carried devices or human tracking sensors embedded in the shop floor environment. The projects are assigned by the planning personnel through the production planning service module. Each project is associated with an ID and a sequence of tasks. Tasks are assigned to workers and resources using the dynamic task scheduling service. The worker ‘type’ refers to the roles that a worker is qualified to carry out, such as machine operator, maintenance, etc. The resource ‘type’ refers to the type of machine, e.g. CNC milling, and the specifications of the machines so that tasks can be assigned to appropriate resources. The ‘status’ of the worker and resource refers to whether they are available or unavailable. Under the task data structure, the worker type, resource type, raw materials required, and the estimated processing time are extracted from data provided by designers and process planners. The task description consists of text-based instructions that guide a worker on the steps to be performed to carry out a task. This is also input by designers and process planners. The OGS is context-aware as it is capable of presenting adapted content to the users based on the specific context.

The OGS module makes use of user and resource location awareness to highlight relevant resources and raw materials and direct the user’s attention to them. Combined with the text-based instructions in the task description, graphical augmentations registered to physical locations in the shop floor can be overlaid on the real scene in the AR viewing device to provide the worker with a comprehensive description of the task. In Figure 3(a), the user is directed to the storage location of the raw materials and the raw materials required for the task are listed and highlighted in the AR scene. In Figure 3(b-c), the user points to items on the storage rack to receive information of these items, such as the item name and part number (Yew, Ong, and Nee 2016).

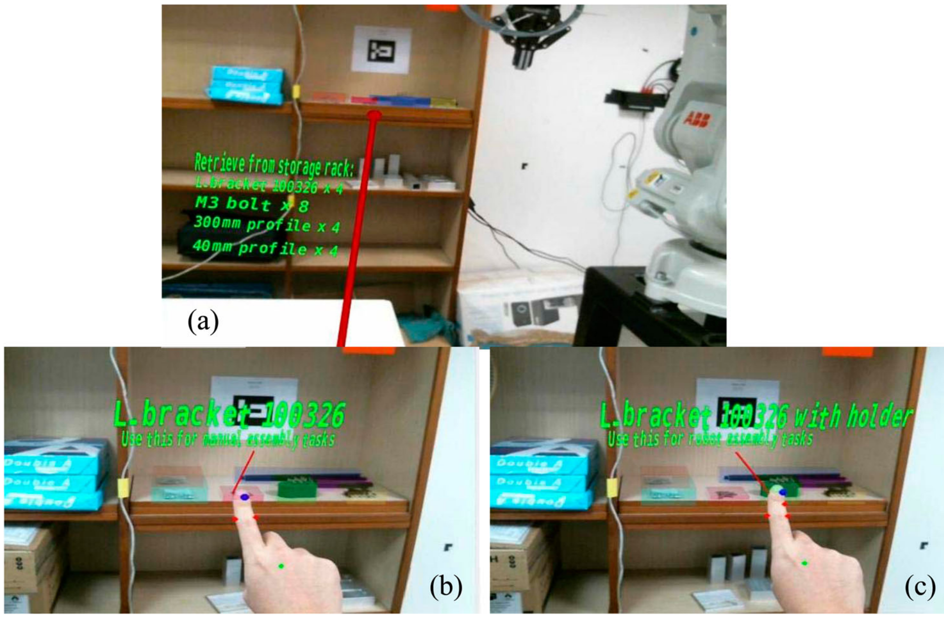


Figure 3. Operation Guidance through AR.

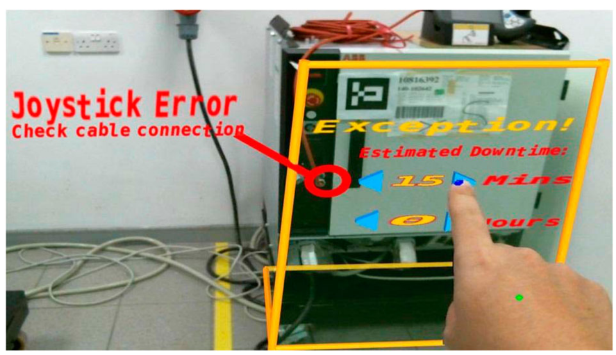


Figure 4. Machine exception AR interface overlaying the machine.

4.4.2. Production planning service (PPS) and dynamic tasks scheduling (DTS)

The PPS module governs project management and responds to asynchronous events on the shop floor. The production manager takes into account the new state of the manpower available when carrying out task scheduling. When a machine breaks down, the process planner creates a maintenance task for that machine and assigns it to the shop floor. The process planner would schedule the maintenance task alongside the other tasks that have been assigned to the shop floor with the DTS module. An AR user interface is displayed over the physical machine, allowing the maintenance worker to interact with the augmented virtual buttons to input the estimated downtime of the machine (Figure 4).

A maintenance task is generated from a maintenance procedures database stored in the memory banks of PPS. The database consists of the error codes that could be output by the machining resources in the shop floor, and the corresponding error description, corrective maintenance operations and location of each operation. For example, in Figure 4, the 'Joystick Error' is an error code of #20224 from the robot controller.

The function of the DTS module is to schedule the sequence of tasks for multiple projects that are to be executed in the shop floor, and re-schedule as the status of the resources and workers change, such as breakdowns and deviation from the original production plan. The workflow of DTS can be stated as follows (Figure 5). In the PPS, when a new project p_j arrives stochastically, the product manager divides the project into m_j sets of tasks T_{ij} in project p_j ($i = 1{,}2, \ldots m_j; j = 1{,}2, \ldots ,n$). The order of tasks in each project is determined, i.e. T_{ij} cannot be processed before its prior task $T_{(i-1)j}$. Meanwhile, the expected task duration for each task is estimated by the product manager and/or based on empirical data, and input by the UAR user interface. In the smart shop floor, there are a set of o stations S_k ($k = 1{,}2, \ldots ,o$). The stations can be categorized into several types based on their functions (e.g. machining, 3D printing, assembly, etc.). The stations in the same type can

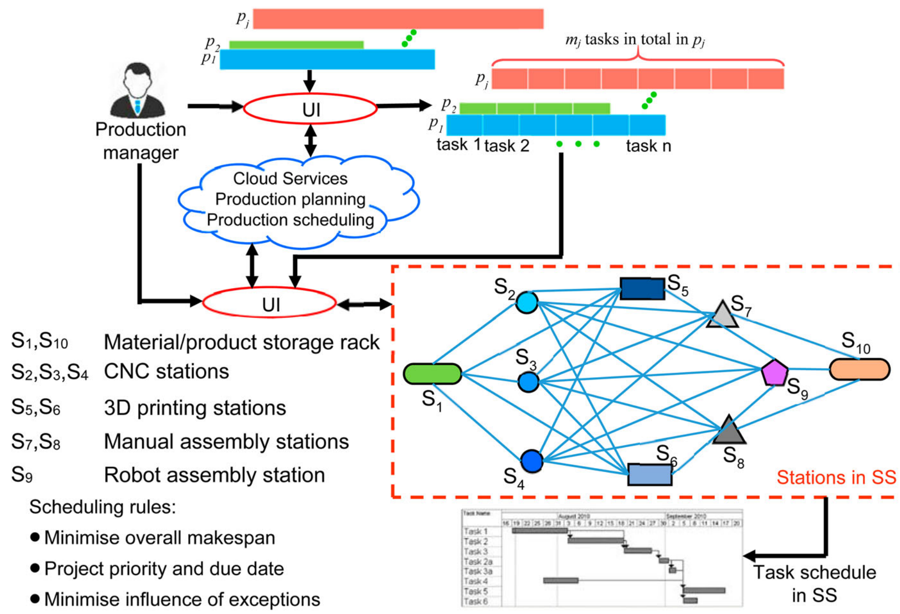


Figure 5. Workflow of DTS in SSUAR.

have different processing capabilities. A representative SS with 10 stations is shown in Figure 5, and the different processing capabilities are represented with different colours.

The DTS module consists of four main steps (Figure 6). First, an initial task sequence is built. The steps can be arranged in a random order or in a specific sequence as an initial solution. The next two steps are performed iteratively based on a pre-determined number N of iterations to execute the optimisation algorithm. The second step is to mutate the task sequence, which method depends on the optimisation algorithm employed. The third step is to decode the task sequence into a schedule. During this step, each task is assigned to a timeslot and specific resources and workers, based on the suitability of workers and resources, their earliest availability, as well as the proximity of the available workers to the relevant resource. The validity of the schedule with respect to satisfying the constraints, such as whether machines have been unloaded before they are loaded for the next process, and precedence relations of the steps, are checked in this step. If constraints are violated, the schedule is rejected and the next iteration begins. The best schedule obtained at each iteration is stored. After N iterations, the best schedule is output.

Due to dynamically changing conditions of the shop floor, the DTS module is executed continuously so as to respond to production progress.

For this research, an iterative particle swarm optimisation (PSO) method was adopted (Eddaly, Jarboui, and Siarry 2016) to optimise task scheduling. Workers, who are equipped with smart device, are informed of tasks via their smart devices that display AR graphics to inform them of the task parameters and locations of the relevant resources and raw materials. The main notations are defined in Table 2.

The objective of the PSO algorithm, as stated in Equation (1), is to find a schedule that minimises the overall makespan ($\mathrm{MS}_{\mathrm{overall}}$), i.e. the time required to complete all projects.

$$\mathrm{Obj} = \min(MS_{overall}) \tag{1}$$

$$MS_{overall} = \max(MS_1, MS_2, \ldots, MS_j) \tag{2}$$

$$st_{ij} = \max(et(T\_pre_{ij}), et_{(i-1)j}) \tag{3}$$

$$et_{ij} = st_{ij} + pt_{ijk} \tag{4}$$

$$MS_j = et_{m_j j} \tag{5}$$

The makespan for all the projects is calculated as the longest MS for each project (Equation (2)). For each Task T_{ij}, the start time is calculated as the end time of the T_pre_{ij} or $et_{(i-1)j}$, where the longer time is used in the calculation (Equation (3)). The end time for T_{ij} is calculated using Equation (4), and the MS_j is calculated using Equation (5), in which m_j is the number of tasks in p_j. It is assumed that two tasks cannot be processed simultaneously in the same station.

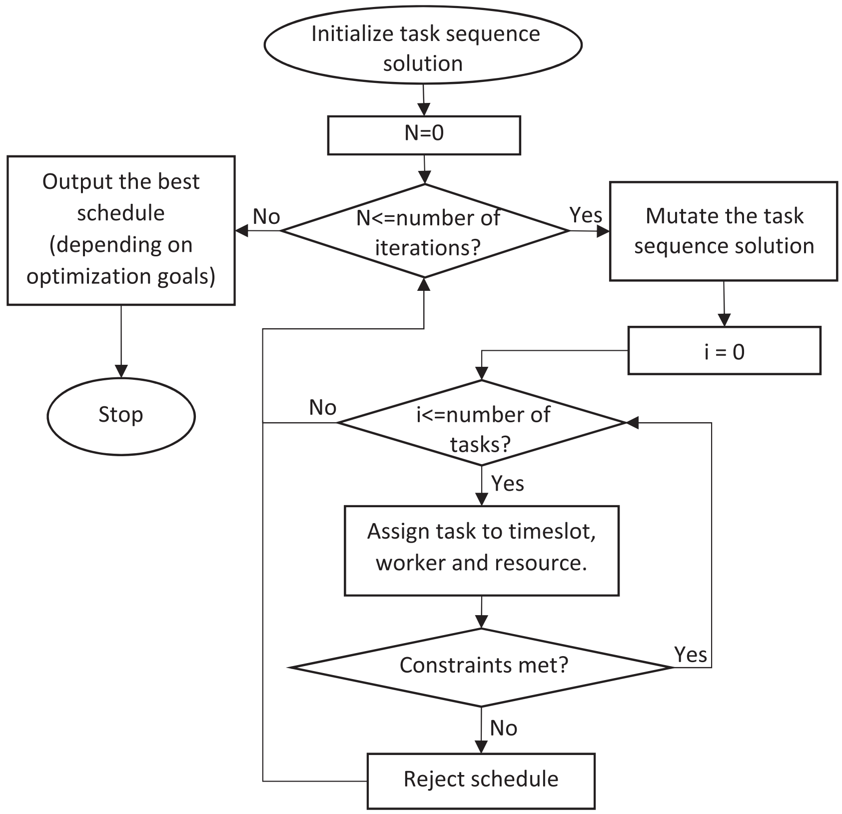


Figure 6. The dynamic task scheduling algorithm.

Table 2. Notations in SSUAR.

p_j	Project j	st_{ij}	Start time of T_{ij}
T_{ij}	Task i in project j	et_{ij}	End time of T_{ij}
T_pre_{ij}	The task just before T_{ij} in the same processing station	delay_{ij}	Delay time of T_{ij}
S_k	Station k in SS	delay_l	Delay time of *lth* station
pt_{ijk}	Processing time of T_{ij} in station k	par_{gh}	The position of *h*th particle used in PSO for function category g
due_j	Due time of project j	par_lb_{gh}	The local best particles set for $par_{1h}, par_{2h}, \ldots, par_{k_0h}$
vel_{gh}	The *h*th particle velocity used in PSO for function category g	MS_j	Makespan for project j
par_gb_{gh}	The global best particles set for $par_{1h}, par_{2h}, \ldots, par_{k_0h}$	$MS_{overall}$	The time required to complete all projects

After production planning, tasks are classified based on the function types of the stations. The sequence of the tasks in a function category g will form a particle par_{gh}. The velocity of the particle par_{gh} is denoted by vel_{gh}, which is a vector having the same number of entries as the corresponding par_{gh}. Each entry of vel_{gh} has a value of either 1 or 0. The algorithm for particle movement can be introduced as sub-routines: (par_{gh}, vel_{gh}) = UPDATE_PARTICLE_POSITION $(par_{gh}, vel_{gh}, par\_lb_{gh}, par\_gb_{gh})$ (Sha and Hsu 2006). Based on the PSO algorithm, the procedure of the task scheduling optimisation in the DTS module is described in Algorithm 1.

Algorithm 1 Dynamic tasks scheduling (DTS) optimisation

During Step 3, the task sequence defined by the particles are decoded into a task schedule, i.e. each task is allocated to a timeslot, worker and resource, and the makespan of each project is computed based on the task schedule. If multiple workers are available during the same timeslot, the task is allocated to the worker who is nearest to the resource that the task has been assigned to. Furthermore, acceptable task schedules must satisfy the following rules:

(1) The makespan for each project is less than or equal to the due time.
(2) Machines must be unloaded before they can be used in the next process.

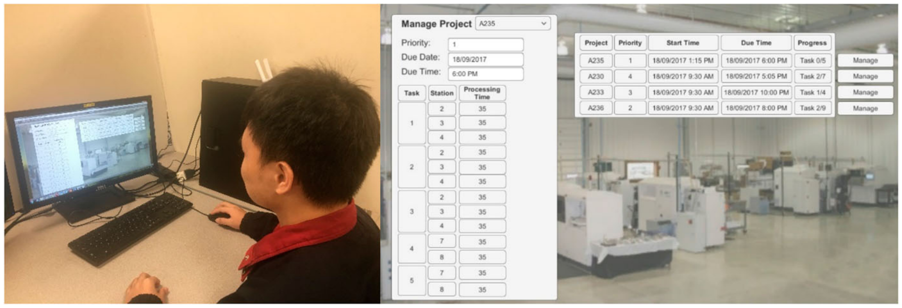
Step 1	Initialization
	For each function category g, initialise a population of K particles with random positions and velocities in the search space
	For function category $g := 1$ to g_0
	K particles: $par_{g1}, par_{g2}, \ldots, par_{gK}$
	K velocities: $vel_{g1}, vel_{g2}, \ldots, vel_{gK}$
	Set par_lb_{gh} and par_gb_{gh}
	$par\_lb_{gh} = \{par_{1h}, par_{2h}, \ldots, par_{k_0h}\}$
	$par\_gb_{gh} = \{par_{1h}, par_{2h}, \ldots, par_{k_0h}\}$
	Set the global best fitness value as a big value, e.g. $g\_fitness = 1000000$ (unit: min)
	Set the local best fitness value as a big value, e.g. $l\_fitness = 1000000$ (unit: min)
Step 2	Determine if there are new insertion projects
	If there are new insertion projects
	Remove the finished and on-going tasks from each particle
	Add the new tasks to each particle
	Go to Step 3
	Else
	Go to Step 3
	End
Step 3	Calculate the fitness value (equation(1)) according to the positions of particles, and update par_lb_{gh} and par_gb_{gh}
	For h: = 1 to K
	Determine the processing time pt_{ijk} for each task T_{ij} in a certain station k according to the task schedule determined by $par_{1h}, par_{2h}, \ldots, par_{k_0h}$
	Calculate the start time st_{ij} for each task T_{ij}according to equation (3)
	Calculate the makespan for each project $MS_1, MS_2, \ldots, MS_j$ according to equations (4-5) and determine the makespan for all the project $MS_{overall}$ according to equation (2) as *fitness_value*
	If fitness_value $<$ *l_fitness*
	Update *l_fitness* = fitness_value
	Update $\mathrm{par\_lb_{gh}} = \{par_{1h}, par_{2h}, \ldots, par_{k_0h}\}$
	If fitness_value $<$ *g_fitness*
	Update *g_fitness* = fitness_value
	Update $par\_gb_{gh} = \{par_{1h}, par_{2h}, \ldots, par_{k_0h}\}$
Step 4	Update position and velocity of the particles
	(par_{gh}, vel_{gh}) = UPDATE_PARTICLE_POSITION $(par_{gh}, vel_{gh}, par\_lb_{gh}, par\_gb_{gh})$
Step 5	Loop to step 3 until a sufficiently good fitness value or a maximum number of iterations.

5. Case Study

5.1. Implementation

For this case study, the three cloud services, PPS, DTS, and OGS have been implemented as separate executable programmes. There are eight stations in the smart shop floor, namely, three CNC stations (S_1, S_2, S_3), two 3D printer stations (S_4, S_5), two manual assembly stations (S_6, S_7), and one robot assembly station (S_8). A server has been developed to link the cloud services and the workers and resources on the shop floor via a TCP/IP network. The workers use a tablet (Microsoft Surface) as the UAR device, and one ABB IRB 140 industrial robot serves as the robot assembly station. The UAR application runs on the surface laptop as well as an Android platform, and communicates with the server to obtain updated data. RFID sensors as well as environment sensors (e.g. temperature, distance, etc.) are distributed in the smart shop floor environment. The other seven stations are not physically available in the test environment, but their presence is simulated so as to demonstrate the operation of DTS. The transportation time among two adjacent processes is negligible.

An Android application has been developed for the tablet to display and interact with the AR interfaces in the shop floor. It uses the Project Tango (Marder-Eppstein 2016) software platform to perform simultaneous localisation and mapping (SLAM), which tracks the pose of the viewing device by building up a 3D map of the physical features of the environment as they are detected by the camera on the device and simultaneously estimating the pose of the device with respect to these features. In addition, fiducial marker tracking (Fiala 2005) is used to anchor the 3D map of the physical features to predetermined locations in the shop floor. This allows the pose estimated by the SLAM algorithm to be expressed with respect to a fiducial marker, and key locations in the shop floor, such as the locations of machining resources and inventory bins, to be expressed in six degrees-of-freedom with respect to the fiducial markers. Thus, the device can track its location with respect to a fixed shop floor coordinate system. Continuous tracking with respect to the shop floor is achieved, even when a



(a) Production manager using PPS (b) The PPS interface

Figure 7. Web interface for PPS.

fiducial marker is not detected, through the SLAM algorithm as long as the pose of the device with the shop floor has been previously established by tracking a fiducial marker.

A standalone executable programme serves as a proxy to the industrial robot. A TCP/IP connection to the robot controller allows this programme to monitor events, such as errors in real-time. When an error occurs, the operation status of the robot is set to 'breakdown has occurred'. This serves two purposes. First, it indicates to the task scheduler that the machine is not able to accept any tasks. Second, it generates AR graphics to indicate to the workers on the shop floor on where the problem might be and suggestions on how to resolve this problem. This is implemented by defining a different set of AR visuals and suggestions by the maintenance expert based on the error code.

5.2. Test scenario

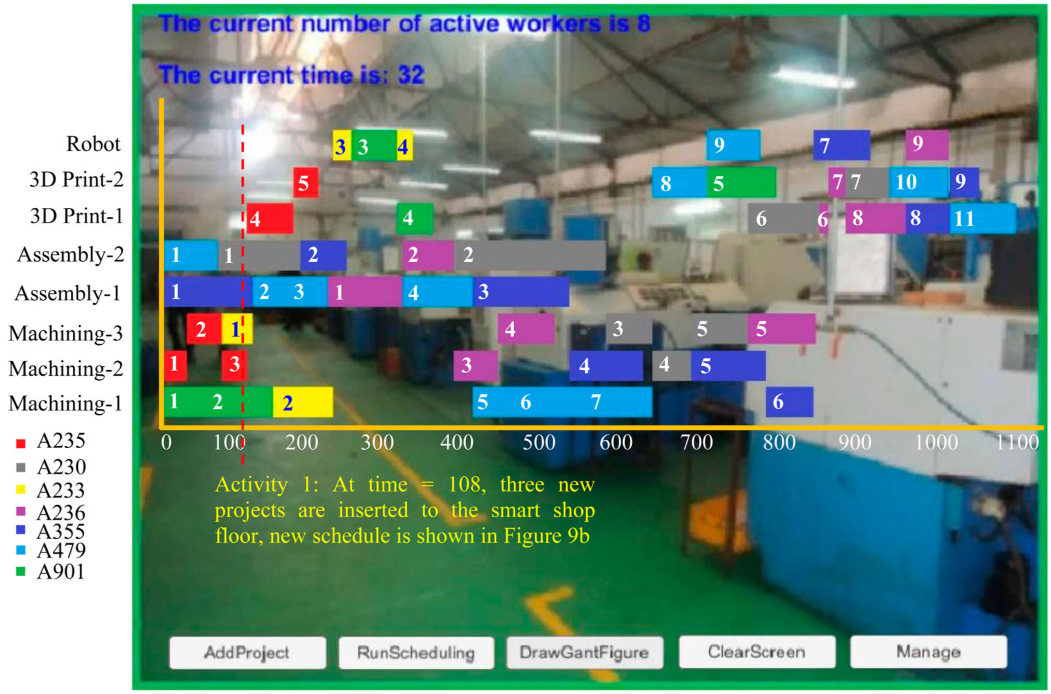
When new projects arrive, the production manager assigns these projects to the SSUAR system, and divide each project into a sequence of tasks, with the estimated processing times and due dates via the PPS module. Figure 7 shows the PPS web interface used by the production manager. After this step, the information of the projects is input to the DTS module, and the tasks schedule is generated using Algorithm 1. In addition, the process planner adds visual operation instructions to each task. The instruction data are stored in the server. Figure 8(a) shows the task schedule for seven projects.

With the task schedule from the DTS module, instructions of each task are provided to the worker that has been allocated that task through the UAR interface that is displayed on his/her smart device. For example, the third task of Project A233 is a robot assembly task. The OGS module generates textual overlays regarding the task due time as well as the steps to carry out the task and places them over the robot assembly station (Figure 9).

During the day, as the smart shop floor is in operation, three new projects arrived. The production manager assigns these projects to the DTS module. Figure 8(b) shows the re-scheduling results. As time is 108 min after the start of the schedule, the scheduling for tasks which are executed during/before that time will not be changed. Later in the day, the robot assembly station breaks down. A worker inputs the estimated delay time to be 600 min via the AR interface and the PPS module assigns a robot assembly repair task to the shop floor. The instructions of this repair task are also sent to the terminal on-site (the tablet) that is used by the remote maintenance expert. Figure 10 shows the whole process to handle the breakdown of the robot station. When the worker is near to the robot station, pertinent task and error information will be displayed as AR contents to the tablet held by the worker (Figure 10(a-c)). The position of the worker is tracked in real time using SLAM. When the on-site worker is near to the robot controller, the instructions will be displayed to guide the worker who is undertaking the errors check and repair tasks (Figure 10(d-f)). After receiving the delay time information from the worker, the process planner re-schedules the tasks using the DTS module such that the remaining robot assembly tasks can only be carried out after the robot assembly station has been repaired (Figure 8(c)). The new schedule and instructions will be sent to the workers. If the actual progress of one/several tasks deviate from the tasks schedule significantly, the progress status (e.g. actual start time, end time of each task, etc.) can be input by the on-site worker using the UAR interface and sent to the process planner. Hence, the process planner can decide whether to re-schedule the tasks.

5.3. Discussion

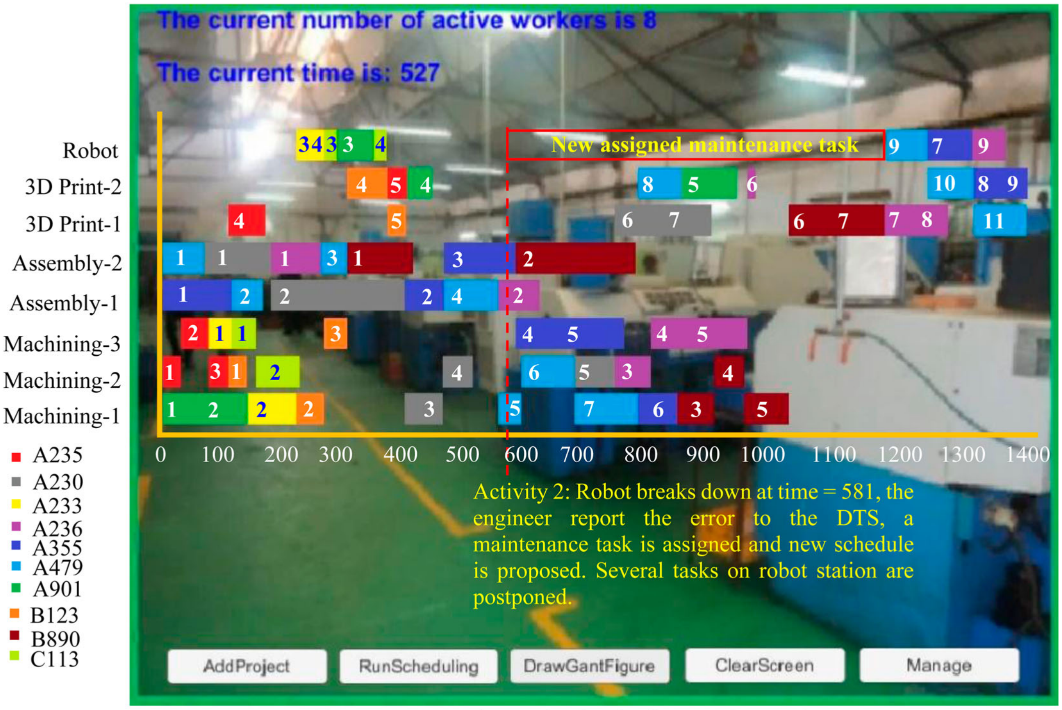
The case study demonstrated the ability of SSUAR to integrate task scheduling with two-way communication between the system and the users. For example, the production manager and process planner assigned the task schedule and instructions to the on-site terminals that are attached to the manufacturing resources (e.g. CNC machines). The on-site workers retrieved pertinent information of the UAR devices and reported the actual task progress information to the management functions modules (PPS and DTS) via these terminals. When the actual task progress information deviated from the task schedule, the tasks would be re-scheduled by the process planner using DTS. When the station broke down (e.g. robot), the process planner would assign the maintenance task to the on-site worker, who estimated the delay time and sent this



(a) Task schedule for seven projects

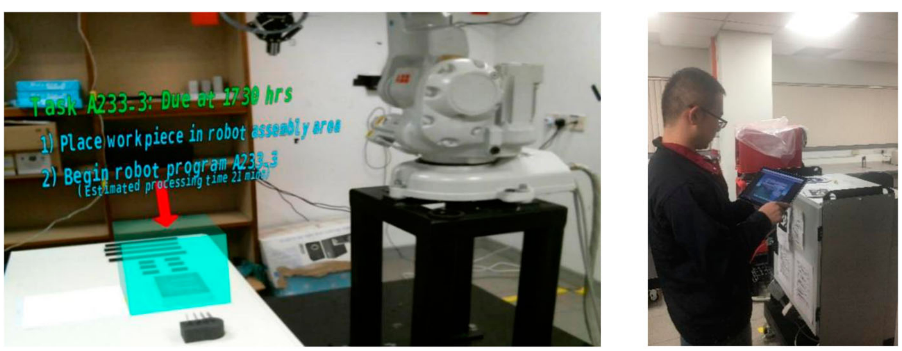
(b) Three new projects are inserted at time of 108

Figure 8. Task schedules output by DTS module.



(c) Response to robot station breaks down at time = 581

Figure 8. Continued.



(a) UAR view (b) UAR interface

Figure 9. Information of the on-going task in the UAR interface.

to the DTS. A new task schedule would be generated to reduce the effect caused by the breakdown. The monitoring of data and user input in real-time is important in ensuring that productivity and efficiency are maintained in the midst of unforeseen occurrences. With the proposed PSO tasks scheduling algorithm running in real time based on the integrated UARF module, the scheduling plan can be transmitted to the on-site users by the TCP/IP network built in the smart shop floor. Any exceptions/disturbances in the smart shop floor can be identified by the on-site users in time and transmitted to the planners directly to reduce their impact. Based on the real-time position information of the on-site workers and the task progress information (e.g. start and end time, delay information, etc.), the OGS module displayed pertinent AR operation instructions to the worker when he/she was near a certain work station. For the next step, OGS module would be able to capture a user's attention, and guide the user's focus point, so that appropriate and necessary guidance information can be provided automatically to increase the operation efficiency. Therefore, compared with previous literature, the proposed SSUAR provides the benefits of real-time information-driven support and management of shop floor activities through ubiquitous interaction between shop floor workers, manufacturing resources and management. The SSUAR is enabled to monitor the production operation in the smart shop floor and modify the production plan in real time taking into consideration the operation information captured by the ubiquitous devices, and thus improve the productivity and efficiency of

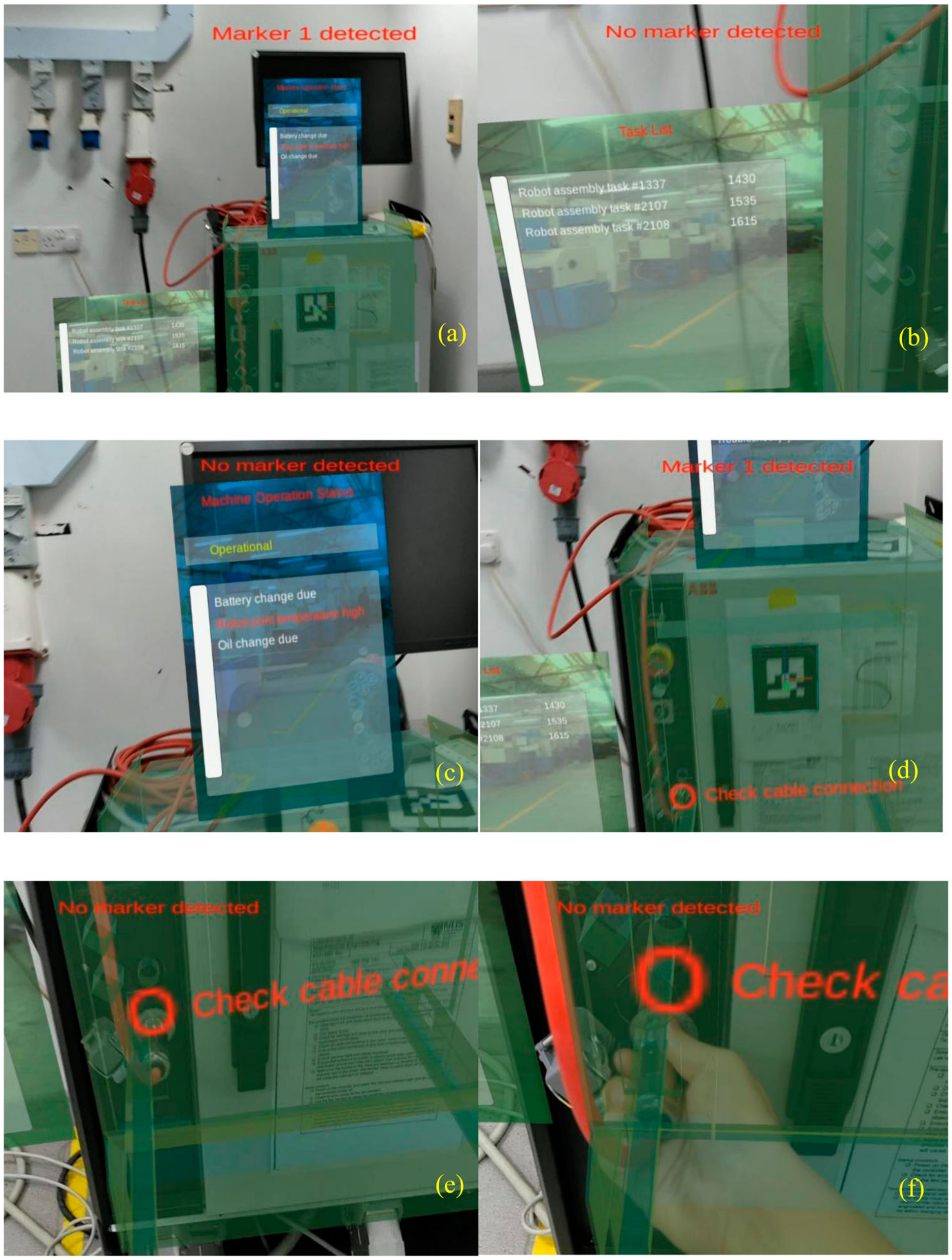


Figure 10. The process to handle robot station breakdown in the smart environment.

the activities in the smart shop floor. In this paper, the authors used two types of tracking sensors, i.e. infrared tracking cameras (OptiTrack: https://optitrack.com/) and inertial tracking system (Perception Neuron: https://neuronmocap.com/). In the proposed system, the sensors are only used in the workspace, which is an open working area, and therefore, the usage of tracking sensors will not raise privacy issues.

6. Conclusion and future work

The SSUAR architecture is a comprehensive architecture of UAR-enhanced smart shop floor system to improve the quality, productivity, and efficiency of a smart shop floor. Multi- services (production planning, dynamic task scheduling and operation guidance) are provided for both on-site users (e.g. machine operators) and off-site users (e.g. process planners). Under this architecture, the shop floor tasks scheduling algorithm can handle the dynamic characteristics of real-time scheduling of tasks in a smart shop floor. The disturbances and exceptions (e.g. unplanned machine failure, deviation from production schedule, etc.) could be captured timely. When a new project is inserted during work time, the system will be able to respond in real time and provide a global optimum task schedule.

The focus of this paper has been on closely integrating task scheduling with real-time data and communication with the users. However, the authors plan to develop additional services to enhance the smart shop floor in different ways. For example, a performance evaluation service and user performance supervision service can be developed to monitor the working habits of the shop floor operators and provide feedback when improvement points are identified so as to enhance the safety of the working environment and the quality of production. It is straightforward to incorporate other variables, such as skills of workers. Different levels of skills of workers can be modelled, and a map built between the worker skills and the time they need to finish a certain task. The consideration of such variables will be included in the future versions of SSUARs. Another area that the authors are developing is multi-modal and natural interaction, where different interaction modalities, such as 3D bare-hand interaction, gaze tracking and voice recognition, can be integrated to enable the users to interact with the system without the distraction of making use of a device to input commands. In addition, the information security issues will be considered in future work, as security issues are important for smart shop floors and cloud services.

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