Digital Twin-based Cyber Physical System for Sustainable Project Scheduling

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Abstract - **In the presence of increasingly dynamic environments, frequent uncertainties, high customer specifications, strict project deadlines, and stricter requirements on sustainability, modern project managers are challenged in their ability to schedule and control projects. Thus, in the context of sustainable project scheduling problem, two important elements are to be considered as decision variables: the input elements of a scheduling (e.g. resources: workforce, machine, money) that enable the realization of a schedule for a project and the output element that are consequences of the realization of the project (e.g. completion time, energy, noise, pollution, waste etc.). In this context, integration of innovative approaches and concepts under the framework of fourth generation industrial revolution is must to build up a sustainable project scheduling model (SPSM). Considering this burning issue, this paper introduces digital twin (DT) technology and cyber physical system (CPS) principles to develop effective and efficient sustainable project scheduling systems and proposes a framework to show how they are interconnected through physical and cyber layers. The proposed framework is also applied to a real-life energy system as a case study for identification of the degradation of a physical layer.**

***Index Terms*- project scheduling, sustainable, cyber physical system, digital twin**

I. INTRODUCTION

Initiated by a high-tech strategy project of the German government, 4^{th} generation industrial revolution (Industry 4.0) integrates physical manufacturing resources with digital network of resources [1]. To cope up with dynamic and global markets: flexible, smart and intelligent manufacturing processed are vital and very much lie at the heart of Industry 4.0. Smart product, smart manufacturing and smart city are some of the main application areas of industry 4.0, including: energy metering and verifying energy conversation [2], software defined cloud manufacturing [3], agile software engineering [4], and lean intelligent production system [5].

Cyber Physical Systems (CPS) can digitally monitor manufacturing systems by creating a digital twin of the physical systems. This CPS-enabled smart manufacturing system can cooperate with humans, machines, sensors and others to make smart decisions through real-time communication [5]. On the other hand, Digital Twin (DT) models the entire manufacturing process or system under consideration as a virtual model and enables bidirectional control with the physical process. DT modelling has provided another promising opportunity to implement smart manufacturing and Industry 4.0 by integrating the cyber and physical worlds in manufacturing [6]. To streamline manufacturing management, Big Data Analytics (BDA) has also been increasingly considered among practitioners and researcher in areas such as statistics, business analytics, data analytics, knowledge discovery from data, data mining, data science and big data [7].

Resource Constrained Project Scheduling Problem (RCPSP) is a well-established project scheduling methodology, more inclined to operational research field (e.g., automobile manufacturing, power generation system, steel production, assembly production scheduling, and job-shop environments [8-10]), in which the principal objective is to minimize project completion time or makespan [11]. To succeed in the digitalized era, integration of intelligent approaches should start from the very early stage of a product's lifecycle. Despite technological innovation and computational advancement, there has been little application of Industry 4.0 or similar methodologies in RCPSP or project scheduling domain. Considering that gap, this paper presents a comprehensive framework to integrate DT and CPS to create a sustainable project scheduling model (SPSM). Contributions stemming from this work are: (i) this is the very first attempt to provide an overview (pictorial structure) of implementing CPS, DT and/or IOT in the project scheduling context; (ii) this proposed framework encompasses sustainability and uncertainty analytics into the SPSM, which will assist the decision maker to take informed decisions; (iii) a degradation identification scheme during the project tenure is provided based on a real-life case study, which can notify the project manager to take mitigation strategy (i.e., sustainable).

The structure of this paper is as follows: section II outlines relevant literatures in the optimisation domain for CPS, DT, IOT and BDA. section III explains a generic CPS integrated DT framework to generate a sustainable project scheduling model. Section IV analyses a real-life case study (Power System Project) to identify the physical layer's degradation to increase the performance of the DT framework. Section V offers a conclusion.

II. LITERATURE REVIEW

The CPS notation can be traced back to 2006-07, when it was first highlighted as a concept of utmost importance for US industrial competitiveness. Different transdisciplinary methodologies such as cybernetics theory,

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mechanical engineering, mechatronics, manufacturing systems and computer science can be an integral part of a CPS [12]. As with Industry 4.0 concepts, CPS concepts have also been applied in a variety of projects in a range of domains. Some notable applications are: power systems [13], water distribution networks [14], civil structure [15], autonomous vehicles [16], intelligent manufacturing systems [17], healthcare [18] and communication [19]. Recent surveys on CPS along with its diverse application can be found in the works of Zhong, et al. [12] and Hohmann and Posselt [20]. The competitive benefits and the underlying methodologies of DT models are like CPS and have five enabling components in the digital model: sensors, physical assets, integration, data and analytics. Some typical application areas are (but not limited to): autonomous manufacturing in smart shop floors [21], flexible robotic assembly lines [22], CNC machine tools [23] and smart injection molding [24].

Both CPS and DT have been recognized as key enablers of smart production and manufacturing systems. While CPS establishes connections between the physical and cyber worlds through successfully implementing internet of things (IoT), the DT provides more realisations regarding the IoT integrated CPS functions [25]. IoT facilitates connection among different physical objects, systems and services, which enables object–to-object communication and data sharing. Radio Frequency Identification (RFID) is one of many examples of IoT techniques—tit is predicted that 20.8 billion devices will be connected and making use of RFID by 2020 [26]. Typical applications of IoT are: smart cities [27], healthcare and social communications [28], machine-to-machine measurement [29] and energy management system [30]. In one application, Tao, et al. [1] implement an IoT enabled manufacturing system for dynamic resource management. They have claimed that their IoT-based smart manufacturing system can provide solutions for complex resource allocation problems in a dynamic manufacturing environment. Even though the BDA technologies have been mature for only few years, there are numerous areas or cases where BDA has been successfully applied. Some of the typical application areas are: internet industries such as Google [31], retailers [32], biopharmaceuticals industries [33], healthcare [34], electric industry [12], aerospace industry [35] and machining optimisation systems [36]. Bilal, et al. [7] have proposed a framework to implement BDA for construction industries. Nevertheless, the framework to integrate CPS, DT and/or IOT in a project management, or more precisely a project scheduling context, is still void, which impedes us to write further literature surveys.

III. Framework To Build A SPSM

Real-life projects are complex and vulnerable to uncertainty. Due to that vulnerability, project scheduling problems need to consider dynamic activity characteristics along with their execution time and varied resource availability. To generate a sustainable project scheduling, practitioners need to understand the dynamics of input parameters (such as resource values, number of activities, and their executive times) to generate output values such as project budget and completion time with minimal computational complexities. Considering complexity or vulnerability of uncertainty among project's data, a project manager (PM) should be vigilant for the real-time data, which can help them to create proactive or reactive (i.e., sustainable) project scheduling. Due to the dynamic nature of manufacturing practice and uneven business goals, there might be billions of data involved in a real-time context. Hence, application of BDA can easily be justified in the project management context.

To ensure a project as sustainable, two important dimensions can be 'designing an economically (e.g., profit or cost) and environmentally (e.g., less water, sound or air pollution) viable project' and 'integrate artificial intelligence or advance intelligence mechanisms in the decision-making process to design proactive or reactive models'. Designing energy-efficient models or optimizing machine usage during activity execution is a good way to develop an environmentally viable project. However, due to the dynamic nature of project parameters, disruptions or breakdowns can happen at any time in a project's lifecycle. Hence, to design a sustainable project, practitioners may need to reschedule at any stage of a project's lifecycle by successfully integrating the latest technologies (i.e., CPS, DT, BDA etc.). To successfully implement digitalized SPSM, the PM needs to identify the cyber and physical components of SPSM. Figure 1 outlines all possible cyber and physical components of SPSM with uncertainty analytics in the middle to ensure sustainability.

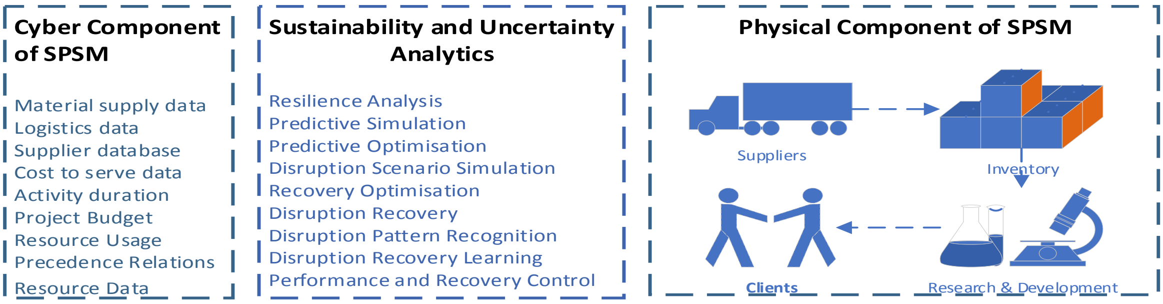

Fig. 1. Layers for SPSM with Uncertainty Analytics

Figure 2 also highlights the CPS integrated DT with both physical and cyber layers. To achieve the key objectives (economic and energy efficiency), this conceptual framework can be implemented, which consists of four components from the perspective of project scheduling context: (i) CPS-enabled real-time data acquisition method, (ii) Big data and IoT enabled architecture to dissolute big data in a solvable format, (iii) uncertain data monitoring module and (iii) Simulation and Optimisation toolbox to solve real-time data and apply rescheduling methods to further tune the preplanned schedule, if abnormalities experienced. The important think about this framework is the approachability and availability of real-time data from all possible terminals under the cyber physical environment, which can potentially help industry leaders to make more accurate and reliable decisions to improve and optimize scheduling decisions throughout a project's lifecycle. Based on the information retrieved from uncertainty data monitoring module, the decision maker will take the necessary action(s) and autonomously inform the 'Simulation and Optimisation Modelling Tool' to obtain results accordingly. Later, the optimised result will then pass to 'Data Analytics' and 'Business Information System' databases for further execution. Hence, the wireless data acquisition system is considered as a backbone of the CPS or DT system to collect real-time dynamic data from a project's perspective (i.e., RFID, IoT sensors). Accumulated data (or big data) can then be transferred through a Wi-fi channel to an internet router or sensor to actuate the processing. From that sensor, all big data is then transferred via a router into the main server for processing. The Hadoop Hive system, a powerful big data storage tool can then be exploited for further processing, instead of traditional data platform such as MySQL. With proper data cleaning, partitioning, visualizing and processing methods, all big data can be exported to the optimization solver. Based on the data received, the existing schedule may need to be modified or rescheduled with the aid of any optimization solver or scheduler to develop a sustainable project scheduling model.

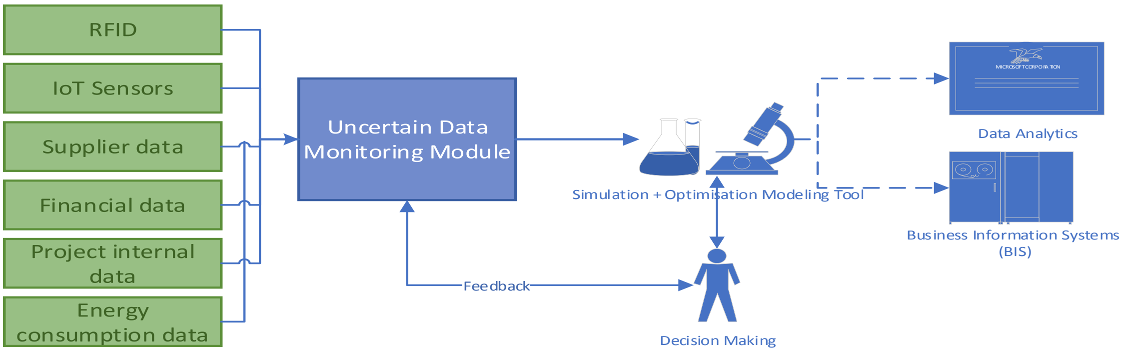

Fig. 2. CPS integrated DT for SPSM

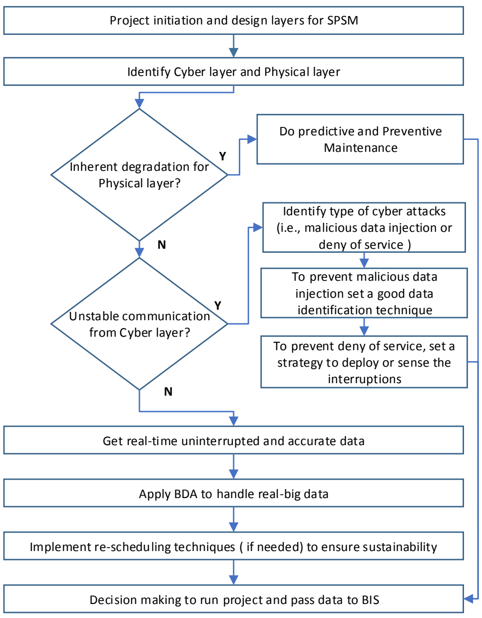

Fig. 3. Handling DT for SPSM

The overall procedure to handle DT for SPSM is explained in Figure 3. Here we consider that the overall performance of DT framweork can be affected predominantly for two reasons: (i) inherent degradation of physical layers and (ii) unstable communication due to cyber-attacks in the cyber layer. Possible solutions to these problems are also highlighted in the Figure. Hence, to build up a successful CPS integrated DT framework for SPSM, suitable precautions and maintenance actions should be prioritized and scheduled beforehand. Therefore, the following section will explain how to identify inherent degradation for any physical layer in the real-life application of power system project.

IV. Case Study for Degradation Identification

A sample power system project is considered with the aim of designing a sustainable project scheduling model. During the project tenure, different sustainability and uncertainty analytics (here degradation of physical layer and unstable communication due to cyber-attacks) are considered. Based on the degradation frequency, a rescheduling framework should be designed, which may include predictive and preventive maintenance schedule. Due to page limitation, reasons and mitigating strategies for cyber-attacks are not considered in this paper. In a distributed generation system, there are 20 generation plants, each of which has different number of gas turbines.

Consider the control block diagram of the cyber physical energy system with both cyber and physical (degraded) components shown in Figure 4. This control diagram represents a typical case consisting of a forward and feedback channel. As these plants are physically distributed, they are operating under different environments; not only the four plants which have the same number of gas turbines, but also even in the same plant, each gas turbine exhibits different degradation paths of efficiency with variations. Frequency deviations over time (in months) are shown in Figures 5 and 6 for single and multiple project types respectively.

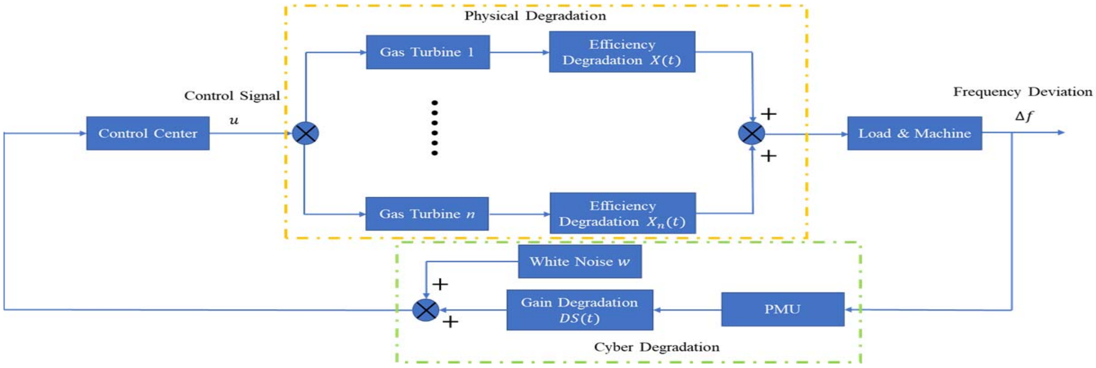

Fig. 4. Control block diagram of the cyber physical energy system

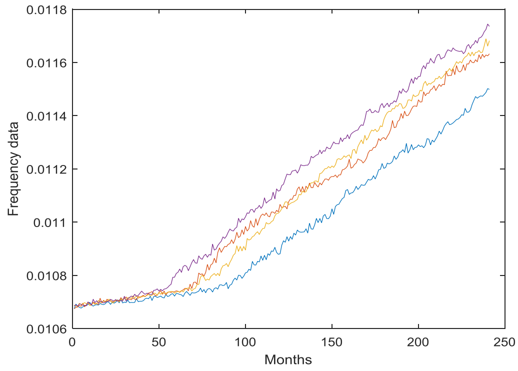

Fig. 5. Variation of sensor data for single project type (2 turbines)

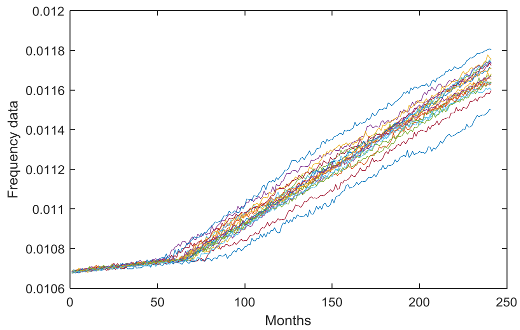

Fig. 6. Variation of sensor data for all project types

This phenomenon can be described by a Wiener degradation model with unit-to-unit variability:

$$X(t) = X(0) + \lambda_1 t^a + \sigma_{B1} B(t) \quad (1)$$

where $X(t)$ is the degradation level of the generator at lifetime t, i.e. the reduction of efficiency or capacity; λ_1 is the drift parameter denoting the aging rate, σ_{B1} is the standard deviation indicating the volatility in the aging process and $B(\mathrm{t})$ is the standard Brownian motion. Without loss of generality, $X(0)$ is equal to 0 at the beginning of the component's lifetime. When $a = 1$, the Wiener degradation model is linear. According to current work, the parameters of the Wiener degradation model for gas turbine are estimated as:

$$\lambda_1 \sim N(0.0043, 0.0005), \sigma_{B1} = 0.0045 \text{ and } a = 1 \quad (2)$$

As the degradation level of gas turbine is underlying, we can only use the sensor measurement, i.e. frequency deviation of power system, to estimate the hidden degradation of gas turbine. However, the sensor measurement also suffers from sensor gain degradation and the inherent measurement error. Therefore, the received sensor measurement (SM) at lifetime t is given as:

$$SM = [1 - ds(t)]\Delta f + w \quad (3)$$

where $ds(t)$ accounts for the stochastic sensor gain degradation, which follows a Wiener degradation $ds(t) = ds(0) + \lambda_2 t + \sigma_{B2} B(t)$. w (Hz) is the normally distributed white noise. According to existing degradation models of PMU, the parameters of Eq. (3) are given as $\lambda_2 = 0.005$, $\sigma_{B2} = 0.0002$ and $w \sim N(0, 2 \times 10^{-11})$. Both physical and cyber degradation, i.e. the generator's degradation and sensor's degradation can lead to the deteriorated DT performance which may result in power system failures, due to the system frequency exceeding its maximum allowable drop (PO) or failing to attain the steady-state frequency tolerance band in the required time (ST) in compliance with ISO 8528–5 [14]. The PM should make use of the collection of measured frequency deviation to ensure the life cycle performance of each area supplied by each generation plant within the thresholds, i.e. $L_{PO} = -0.0115$ pu and $L_{ST} = 30$ s. Based on this degradation data, a PM needs to develop a predictive or reactive preventive maintenance schedule to ensure better life expectancy of physical layers (i.e., sensors, actuators etc.). In case of cyber-attacks, practitioners need to set up a good data-identification technique and an intelligent sense to deploy those interruptions. After ensuring damage and attack-free DT layers, 'Uncertainty Data monitoring Module' can successfully read dynamic data and pass it to 'Simulation and Optimisation' tool for decision making.

V. Conclusion

Focusing on the increasing attention of Industry 4.0, CPS, BDA, IoT and DT concepts, this paper proposes a generic framework to integrate CPS into a DT framework in order to create a sustainable project scheduling model. The motivation behind the proposed model has been explained by shedding light on the development of intelligent manufacturing concepts. In order to be sustainable in the presence of dynamic real-time variations, integration of advanced intelligence approaches is essential, which can be implemented by the proposed framework. This proposed SPSM framework is further analyzed with degradation identification scheme with a practical power system project as a case study. However, in this case, exploration of better optimization approaches and how to solve big data is out of the scope and could potentially be a future research direction.

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