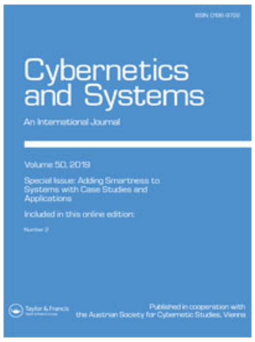

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Decisional-DNA Based Smart Production Performance Analysis Model

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ABSTRACT
In order to allocate resources effectively according to the production plan and to reduce disturbances, a framework for smart production performance analysis is proposed in this article. Decisional DNA based knowledge models of engineering objects, processes and factory are developed within the proposed framework. These models are the virtual representation of manufacturing resources, and with help of Internet of Things, are capable of capturing the past experience and formal decisions. A case study for the smart tool performance analysis is presented in which information of key tool parameters like tool life, surface integrity, tool forces and chip formation can be sensed in real-time, and predictions can be made according to specific requirements. This framework is capable of creating a cyber-physical conjoining of the bottom-level manufacturing resources and thus can work as a technological basis for smart factories and Industry 4.0.

KEYWORDS
Decisional DNA; Virtual Engineering Factory (VEF); Virtual Engineering Object (VEO); Virtual Engineering Process (VEP)

Introduction

Massive research efforts have been recently carried out to add smartness to manufacturing processes and towards the adoption of forth industrial revolution, Industry 4.0 (Shafiq et al. 2017; Zhang et al. 2016; Zhang et al. 2017). In this direction, agent technology has been widely developed and implemented in manufacturing applications for its autonomy, flexibility, reconfigurability, and scalability (Maturana et al. 2004). Related works on the implementation of multiagent systems into industries were extensively conducted in different fields including process and quality control, object management, manufacturing control systems etc. (Zhang et al. 2011). Valckenaers et al. extended the concept of intelligent agents to intelligent

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beings, which focuses on not only on the capabilities of decision making but also reflect the physical reality (Valckenaers et al. 2007). In order to apply web services in factory automation, the theoretical foundations, including the resource virtualization method, the semantic web, and the service composition method, were also studied (Tao et al. 2013). Recently, many emerging technologies are greatly promoting the development of Internet of Things (IoT) (Want, Schilit, & Jenson 2015), including radio frequency identification (RFID), near-field communication (NFC), Bluetooth LowEnergy, long term evolution - advanced (LTE-A), etc. Lee et al. and Bagheri et al. proposed the Cyber Physical System (CPS) architecture for Industry 4.0 (Lee, Bagheri, & Kao 2015) and for self-aware machines in Industry 4.0 environment (Bagheri et al. 2015).

Currently, with the applications of new technologies such as RFID, Bluetooth, Wi-Fi, and GSM etc., the new era of the IoT is created (Want, Schilit, & Jenson 2015). It refers to uniquely identifiable objects (things) and their virtual representations in an Internet-like structure. With the support and application of IoT technology, the potentially intelligent and real-time operators of 4C (i.e., perception and Connection, Communication, Computing, and Control) to both physical and virtual objects can be realized (Lopez, Ranasinghe, & Harrison 2012). Thus, by extending the IoT technologies such as RFID and Barcode to the manufacturing environment, real-time and multi-source manufacturing data has become more accessible and ubiquitous (Sanin et al. 2018).

However, the traditional manufacturing systems with centralized and hierarchical control approaches "present good production optimization," but are weak in response to changes (Leitão & Barbosa 2014). Therefore, in this research, a framework on self-adaptation that includes dynamic task allocation, adaptive scheduling, and evaluating the capabilities of dynamic reconfiguration of an industrial system is proposed. CPS provides a theoretical framework for mapping the manufacturing-related things to the computing space so that the modeling of manufacturing systems can be easily achieved. The proposed framework consists of Decisional DNA based knowledge models of engineering objects, processes and factory termed Virtual Engineering Object (VEO), Virtual Engineering Process (VEP), and Virtual Engineering Factory (VEF), respectively. These models are not only capable of capturing real-time information of the shop-floor but also store and reuse this knowledge for future predictions. The significance of this work is that the upper-level management can get important information about the dynamic changes of the manufacturing execution in real time.

The structure of the article is as follows: In the next section, the knowledge representation technique of Set of Experience Knowledge Structure (SOEKS) and Decisional DNA (DDNA) is briefly introduced with a number of references for readers unfamiliar with this technique. The concepts of VEO, VEP, and VEF are explained in the following sections. Next, details of the proposed framework are presented. Then, a case study of the smart tool performance analysis is demonstrated. And the last section summarizes and presents the conclusions drawn from this work.

Set of Experience Knowledge Structure (SOEKS) and Decisional DNA

The powerful knowledge representation technique of Set of experience knowledge structure (SOEKS) and Decisional DNA (DDNA) is used as the technological base for this work. SOEKS-DDNA (Sanín et al. 2012; Sanín et al. 2009; Sanin et al. 2012; Shafiq, Sanin, and Szczerbicki 2014) is a unique and single structure for capturing, storing, improving and reusing decisional experience. DDNA name is a metaphor related to human DNA, and the way it transmits genetic information among individuals through time. The Decisional DNA consists of stored experienced decision events (i.e. experiential knowledge) that can be grouped according to areas of decision or categories. In other words, each SOE (short form for SOEKS) related to a formal decision event can be categorized and acts similarly to a gene in DNA. A gene guides hereditary responses in living organisms, as a SOE directs responses of certain areas of the organization. Furthermore, assembled genes create chromosomes and human DNA, as groups of categorized SOE create decisional chromosomes and Decisional DNA.

VEO/VEP/VEF: Conjoining of the Physical and the Virtual World

The central idea of our concept is to replicate knowledge and experience of the manufacturing factory, and to represent it virtually to create Manufacturing DNA. In a manufacturing domain, a factory performs various processes; a process, in turn, uses different resources for its manufacturing. For the complete knowledge representation of a manufacturing system it is categorized into three levels; first is the resource/object level, second is the process level and third is the factory/system level. SOEKS based knowledge representation of these levels is developed both at the individual level and in conjunction with each other. Virtual/knowledge representation of engineering objects, processes and system will be beneficial in the asset, machine and entire system optimization respectively. Critical, effective and creative decisions can be made based on these intelligent virtual manufacturing levels. In the subsequent sections concept of VEO, VEP, and VEF are discussed.

Virtual Engineering Object (VEO)

A VEO (Shafiq, Sanin, & Szczerbicki 2014; Shafiq et al. 2015, 2015a) is knowledge representation of an engineering artifact. It has three features: (i) the embedding of the decisional model expressed by the set of experience, (ii) a geometric representation, and (iii) the necessary means to relate virtualization with the physical object being represented.

A VEO is a living representation of an object capable of capturing, adding, storing, improving, sharing and reusing knowledge through experience, in a way similar to an expert in that object. A VEO can encapsulate knowledge and experience of every important feature related to an engineering object. This can be achieved by gathering information from six different aspects of an object viz. Characteristics, Functionality, Requirements, Connections, Present State and Experience (Shafiq, Sanin, & Szczerbicki 2014; Shafiq et al. 2015). The technique of SOEKS-DDNA provides VEO the dynamicity to overcome issues of representing complex and discrete objects (Shafiq et al. 2015a).

The changing machining conditions, such as spindle thermal deformation, tool failure, chatter, and work-piece deformation induced by clamping force, cutting force and material inner stress have a significant impact on machining quality and efficiency. VEO will cater decision making regarding these problems which may emerge during the machining process due to complex conditions at the machining level (Sanin et al. 2017).

Virtual Engineering Process (VEP)

Virtual engineering process (VEP) is a knowledge representation of the manufacturing process/process planning of artifact having all shop floor level information regarding operations required, their sequence and resources needed to manufacture. VEP deals with the selection of necessary manufacturing operations and determination of their sequences, as well as the selection of manufacturing resources to "transform" a design model into a physical component economically and competitively (Shafiq et al. 2015b).

As process planning representation, VEP is a combination of information regarding the operation required, manufacturing sequence, and machines involved (Chen et al. 2011). In addition to this, information of all the VEOs of the resources associated with the given process is also linked to VEP. Therefore, to encapsulate knowledge of the above mentioned areas the VEP is designed having following three main modules: (i) Operations (ii) Resources, and (iii) Experience (Sanin et al. 2017). Both VEO and VEP are embedded in cloud computing platform (see Figure 1) to facilitate delivery of compressed information on complex interrelationships within modeled processes.

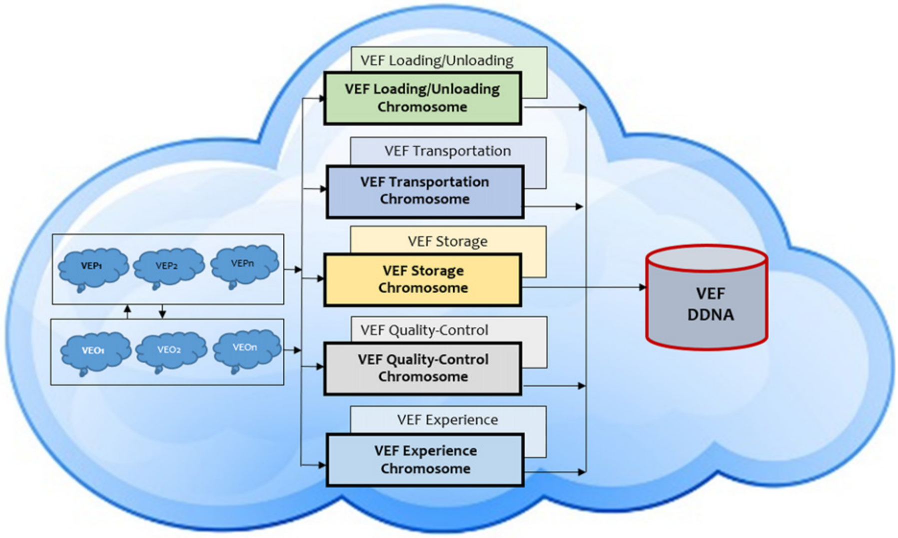

Figure 1. VEF architecture linking VEO and VEP.

Virtual Engineering Factory (VEF)

As shown in Figure 1, a manufacturing factory is a collection of integrated equipment and human resources, whose function is to perform one or more processing and/or assembly operations on a raw material, part, or set of parts (Shafiq et al. 2016). Based on the components and their functionality at the factory level, the architecture of VEF is conceived. VEF has six elements each having links to involve VEP and VEO to represent the entire knowledge and experience of a manufacturing factory. The arrangement of these six elements of VEF along VEO and VEP in a cloud architecture is shown in Figure 1. Elements of VEF are as follows: (i) Loading/Unloading (ii) Transportation (iii) Storage (iv) Quality Control, and (v) Experience (Sanin et al. 2018).

Each factory level experience (i.e. VEF-SOEK) is associated with a component experience (VEP-SOEKS) to be manufactured and that component, in turn, needs machines/objects experience (VEO-SEOKS) for its manufacturing. This idea is shown in Figure 1, VEF-DNA is created by collecting, connecting and linking VEF, VEP, and VEO (Shafiq, Szczerbicki, & Sanin 2018).

Framework for Decisional DNA Based Production Analysis Model

IoT technologies are increasingly widely used in the manufacturing systems to collect real-time data captured by sensors. To efficiently use this data we need extensive research on modeling the dynamic status of a manufacturing system for real-time production performance analysis. In this analysis process abnormal event diagnosis is crucial to ensure normal production operations. In the current practice, decision-making is based on the understanding of a manufacturing process by an expert and is thus subjective. How to dynamically provide managers with qualitative and quantitative exception information such that it is persuasive and objective is a critical issue that has not been solved yet. In the proposed framework information is collected through agents like sensors, RFID, Camera, Operator etc. at three levels of manufacturing setup namely object level, process level and factory level. At the object level, the information is stored in a structured format of SOEKS to create VEO a specialized form of CPS (Figure 2).

An engineering process involves various process parameters along with many resources. Thus, at the process level information along with VEOs create VEP, a specialized form of Cyber Physical Production System (CPPS). At the next level VEF, which is an encapsulation of all the VEOs and VEPs is developed. Finally, as shown in Figure 2, the collection of VEOs, VEPs, and VEF forms Factory Experience or Manufacturing DNA, through which exception information can be extracted.

Manufacturing process can be monitored in real-time, the obtained data can be mined and corresponding knowledge can be discovered to enhance production analysis and exception diagnosis. This is done by systematically

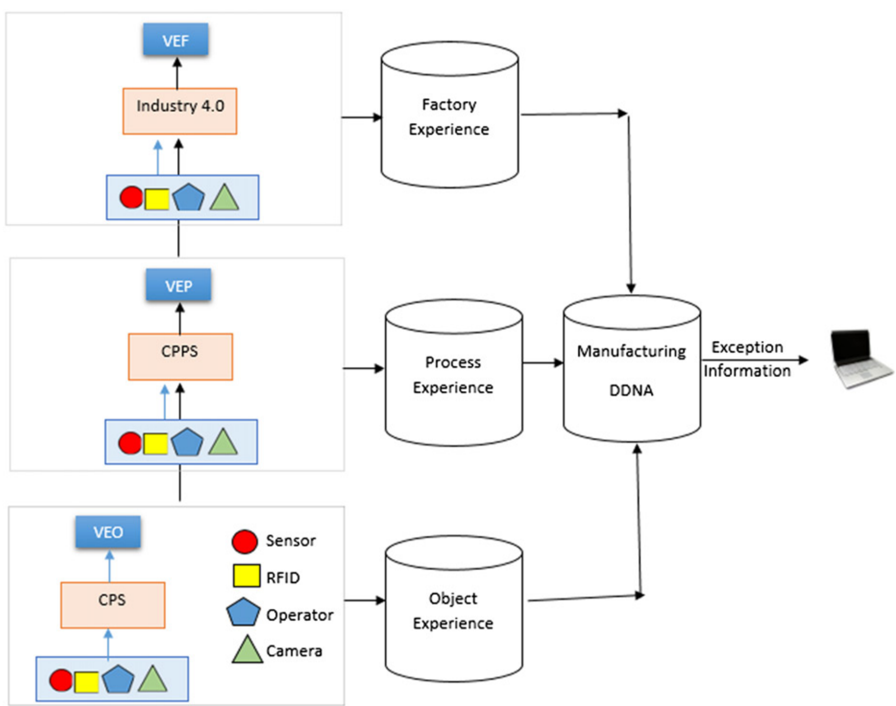

Figure 2. Overview of creating Manufacturing DNA.

deploying RFID devices on the shop-floor to track and trace manufacturing objects and collect real-time production data.

The VEO or cyber-physical machine module is responsible for capturing multisource and real-time manufacturing information around the machine by using auto identification technologies. The aim of this module is to enhance the sensing ability of traditional manufacturing machines. By applying the advanced IoT technologies (e.g., RFID, digital caliper, pressure sensor, etc.), traditional machines are enabled to capture the real-time manufacturing information proactively. These data streams are provided to the VEO/VEP/VEF modules and can be further interpreted as manufacturing progress or state indications. To demonstrate this concept a detailed case-study is presented in the next section.

Smart Machining Tool: A Case Study

In this section, a case-study is presented to demonstrate how a tool in a machining domain of production can be managed in a smart way. Manufacturing any component in a factory requires a combination of different processes and machines/resources. Figure 3 shows the interrelation between the VEOs, VEPs, and VEF in a machining set-up. Not only experience discovery can be made of the individual modules but also the footprint of any decision can be traced. The framework also guides the interrelation between the tool (VEO (Tool)) and the machine, also the process the machine is performing (VEP (Machining)) and lastly the component that is being manufactured (VEF). For a tool "VEO (Tool)-DNA" is

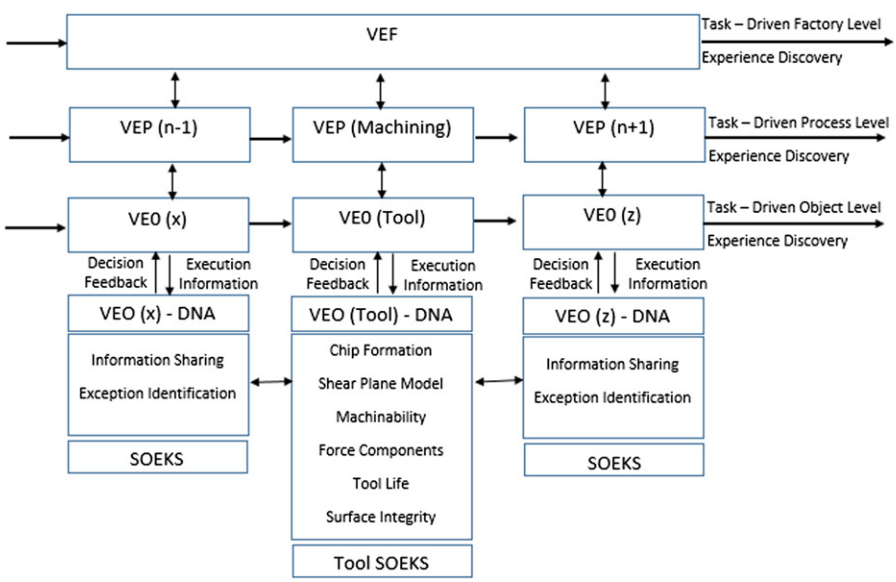

Figure 3. Mechanism of experience discovery in Manufacturing DNA.

first developed and its position in the entire manufacturing scenario is shown in Figure 3. VEO (Tool)-DNA comprises of chromosomes of chip formation, shear plane model, machinability, force component, tool life and surface integrity. These can be modified according to the specific situation and need. Similarly, VEP for process and VEF for manufacturing a component in a factory are developed.

Figure 4 shows the internal architecture of VEO (Tool)-DNA. It has SOEKS of different aspect which affects the tool chromosomes discussed earlier. For example, Material SOEKS have various variables like material type, microstructure, chemical configuration, strength property, and heat treatment. Each SOEKS apart from these variables, have functions, constraints and rules that govern the SOEKS. Similarly, Machine Tool, Production Condition, Tool, Work-piece, and Cutting Material have a number of SOEKS variables as shown in Figure 4.

Data captured for various tool modules (see Figure 4) through various agents like sensor, RFID, CPS and operators is stored in the SOEKS format in CSV format. A parser is written in JAVA programing language to read this data and to convert this information into SOEKS.

In real-time key performance indicators can be monitored and in case of an exception, diagnosis mechanism may be suggested. Figures 5 and 6 shows the output parameters for Tool Life and Surface Roughness calculated from the SOEKS input variables. An operator can set upper and lower

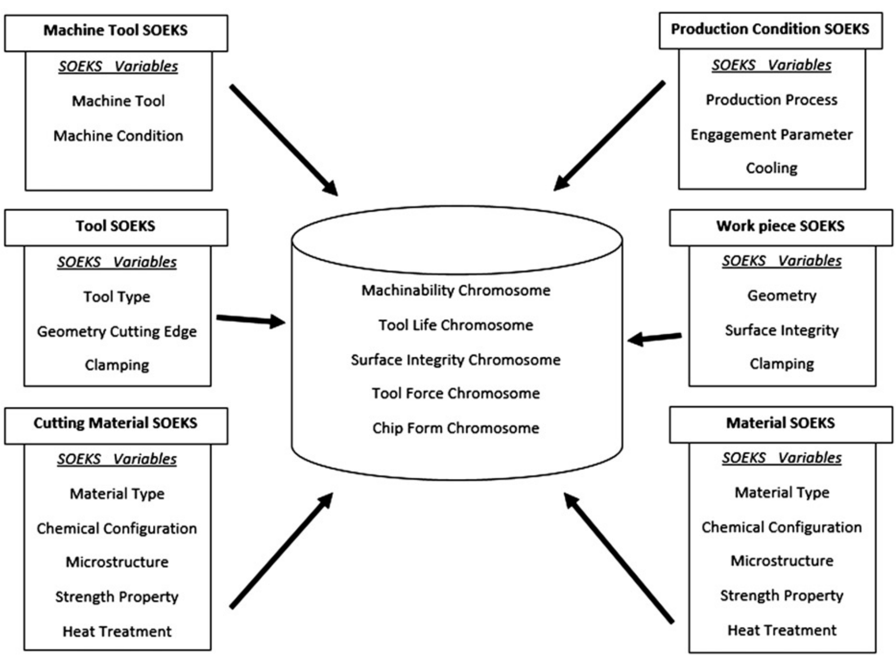

Figure 4. Internal architecture of VEO(Tool)-DNA.

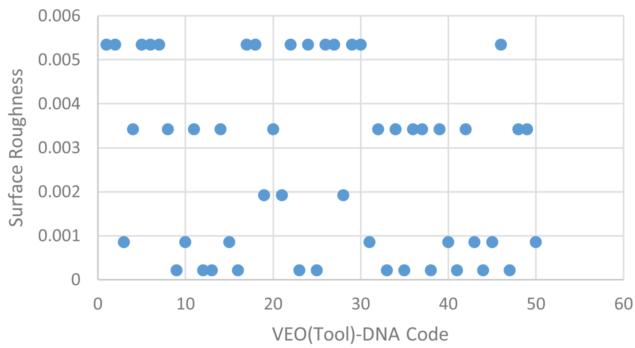

Figure 5. Surface Roughness corresponding to different tool operations.

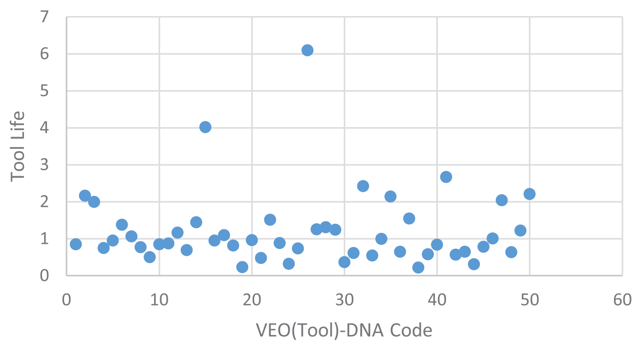

Figure 6. Tool Life corresponding to different tool operations.

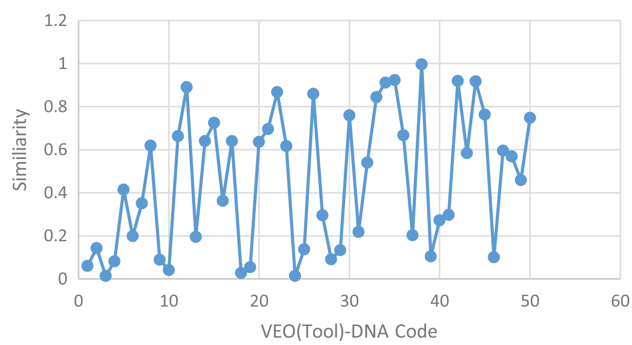

Figure 7. Similarity index for a sample query.

limits for Tool Life and Surface Roughness and analyze the tool settings in case the values are out of these limits.

Another feature of Decisional DNA is that it can be used for prediction. For prediction of a specific situation for tool life and surface roughness, VEO (Tool)-DNA can be queried. JAVA parser calculates the Euclidian distance between the query SOEKS and the VEO (Tool)-DNA SOEKS and gives a similarity index as shown in Figure 7. Once the most similar SEOKS is determined the entire history of that experience can be traced providing the corresponding information for the VEP and VEF.

Conclusions

In this article, we introduced an initial approach that allows IoT and the Decisional DNA to capture decisional events of engineering objects, process and factory and reuse these captured events for decision making in future operations. In this approach, the Decisional DNA is used as the technology of knowledge representation of certain decisional events. Moreover, the adaptability and usability of the Decisional DNA applied to smart production performance analysis model has been tested through a case study of a machine tool in a manufacturing set-up. In future research, we plan to refine the model by evaluation and comparisons of different knowledge discovery approaches.

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