Decisional-DNA-based Digital Twin implementation architecture for Virtual Engineering Objects

Syed Imran Shafiq[a*], Cesar Sanin[b], Edward Szczerbicki[c]

[a]*Faculty of Engineering and Technology, Aligarh Muslim University, India. email: sishafiq.bp@amu.ac.in*

[b]*Australian Institute of Higher Education, Sydney, Australia*

[c]*Faculty of Management and Economics, Gdansk University of Technology, Poland*

Abstract: Digital twin (DT) is an enabling technology that integrates cyber and physical spaces. It is well-fitted for manufacturing setup since it can support digitalized assets and data analytics for product and process control. Conventional manufacturing setups are still widely used all around the world for the fabrication of large-scale production. This paper proposes a general DT implementation architecture for engineering objects/artifacts used in conventional manufacturing. It will empower manufacturers to leverage DT for real-time decision-making, control, and prediction for efficient production. An application scenario of Decisional-DNA based anomaly detection for conventional manufacturing tools is demonstrated as a case study to explain the architecture.

Keywords: Digital Twins (DT), Decisional-DNA (DDNA), Virtual Engineering Objects (VEO)

1. Introduction

A large-scale conventional manufacturing setup consists of numerous engineering objects like machine tools, accessories, and holding devices. The benefits of conventional manufacturing include low initial setup costs and economical fabrication. Nevertheless, it is plagued with inherent uncertainties and difficulties pertaining to product quality and productivity. Defects and unwanted features can affect surface roughness and mechanical properties, apart from many other technical issues that arise during production. Ever since the exponential rise in the advancement in Information and Communication Technologies (ICT) and digitalization, Conventional manufacturers have been looking for feasible solutions to these problems based on Industry 4.0 environment in general and the digital twin (DT) concept in particular [1]. The aim is to exploit the knowledge gained from cutting-edge sensor technologies into DTs to monitor, predict and control manufacturing objects/operations in a traditional setup. Variables that affect part reproducibility, process repeatability, and quality assurance can be empowered with DT [2]. There are various definitions of DT that are provided by researchers from time to time, one of the most accepted definitions of DT has been provided by ISO for ‘‘Digital twin in manufacturing” as ‘‘a fit-for-purpose digital representation of manufacturing key performance indicators (KPIs) element with synchronization between the Observable Manufacturing Entities (OMEs) and its digital representation [3].” In this context, OMEs are conventional manufacturing artifacts, equipment and products. The digital representations are data-based models and simulations to help make responsive and adaptive control decisions.

Data analytics, such as physics-based, data-driven, and physics-informed data-driven modeling, have become valuable tools for employing the digital twin concept when considering digital representation methods for two reasons [4,5]. First, process monitoring and control have been made easier by the growing availability of precise, affordable sensing technology (such as machine vision) that can be quickly implemented into manufacturing facilities [6]. Second, the improvements in computing competencies have made real-time data analysis more practical and effective.

DT can manage manufacturing inherent uncertainties, complexities, and defects through data analytics, enabling real-time analysis and control of the manufacturing process.

But, two problems need to be looked into. First, carrying out multidisciplinary modelling and simulation involves iterative analyses established on a vast, structural-and-material design-space exploration. In addition, several process parameters demand a vast number of sample input data. Second, implementing a DT for the conventional manufacturing process/parts involves integrating multiple systems across different platforms and dealing with interoperability and integration problems [3].

Using a cheap but less accurate model, known as a surrogate model, is one way to reduce the significant processing effort required for physics-based modelling. Experience-based knowledge representation modelling techniques can be applied, such as Decisional DNA (DDNA) and Set of Experience Knowledge Structure (SOEKS), to address above mentioned problems [7-8]. A system architecture that permits the use of such technologies and standards is necessary. Establishing a DT can reduce the number of trial-and-error testing, faults, and manufacturing lead times, resulting in a more efficient strategy. A DT implementation architecture for DDNA-SOEKS based virtual engineering objects (VEO) used in conventional manufacturing (Digital Twin Manufacturing Framework) and the digital thread concept [1] is proposed in this paper. It aims to allow manufacturers to use DTs for real-time decision-making and control of the manufacturing process. It offers a means to tackle complex technologies and procedures that can support implementation.

The architecture is designed to be generic, customizable, and reusable. The remainder of this paper is organized as follows. In section 2, the concept of VEO is discussed. Section 3 introduces the proposed DT implementation architecture. Section 4 demonstrates a case study of anomaly detection in the Virtual Engineering Object (VEO). Section 5 presents the discussion and conclusion.

2. Virtual Engineering Object (VEO)

A VEO is a knowledge representation of the engineering artifact along with its Experience embedded in it. The goal of VEO is to organize the Experience of engineering objects in a flexible standard format. Thus, converting the Experience into helpful information can help practitioners better focus on solving the problems without spending undue time gathering information, modelling it, and then analyzing it. SOEKS and DDNA [7,8], an intelligent knowledge-based decision tool, is used for developing VEO. That means a VEO is not only a knowledge repository but has SOEKS-DDNA qualities like self-awareness and reflexivity embedded in it. A VEO is a knowledge representation of an engineering artefact and it has three features:

(i) the embedding of the decisional model expressed by the set of experiences,

(ii) a geometric representation, and

(iii) the necessary means to relate such virtualization with the physical object being represented.

A VEO can encapsulate knowledge and Experience of each vital feature related to an engineering object. This can be achieved by gathering information from six aspects of an object:

Characteristics, Functionality, Requirements, Connections, Present State, and Experience, as illustrated in Figure 1.

The prospects for applying virtual representation to manufacturing are up-and-coming as it offers a systematic approach to capturing, storing, distributing, and reusing information to make it available, actionable, and valuable to others. This approach will help practitioners make effective decisions at every stage involved in manufacturing based on past Experience, which will enhance industrial design and manufacturing. Moreover, manufacturing DNA can also be developed [9,10,11].

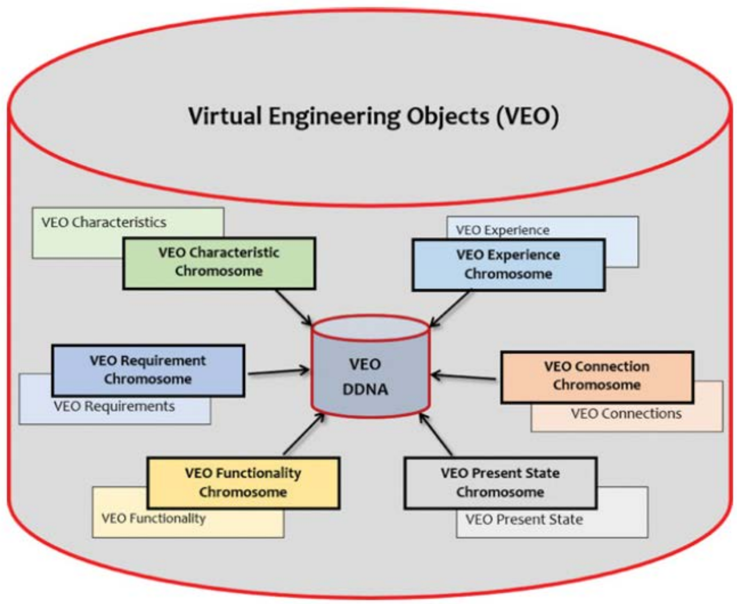

Figure 1: Architecture of VEO

3. DT Implementation architecture of Virtual Engineering Object (VEO)

The proposed DT implementation architecture for VEO in industrial processes is shown in Figure 2. This architecture comprises the components needed by DTs, including real-time process monitoring and control, connectivity, predictability, adaptability, intelligence, and humans-in-the-loop [11]. Additionally, it has two features: a physical twin (PT) and a digital twin (DT). Each layer has one or more entities, each of which is composed of a number of sub-entities and modules. The entities are the VEO-(DNA), data collection and device control, semantic analysis, and user interface manufacturing key performance indicators (KPIs) parts. The presented architecture enables end users to:

(i) depict the real-time VEO situation,

(ii) monitor, control, and anticipate the VEO using data analytics, and

(iii) collect and send VEO data to support decision-making.

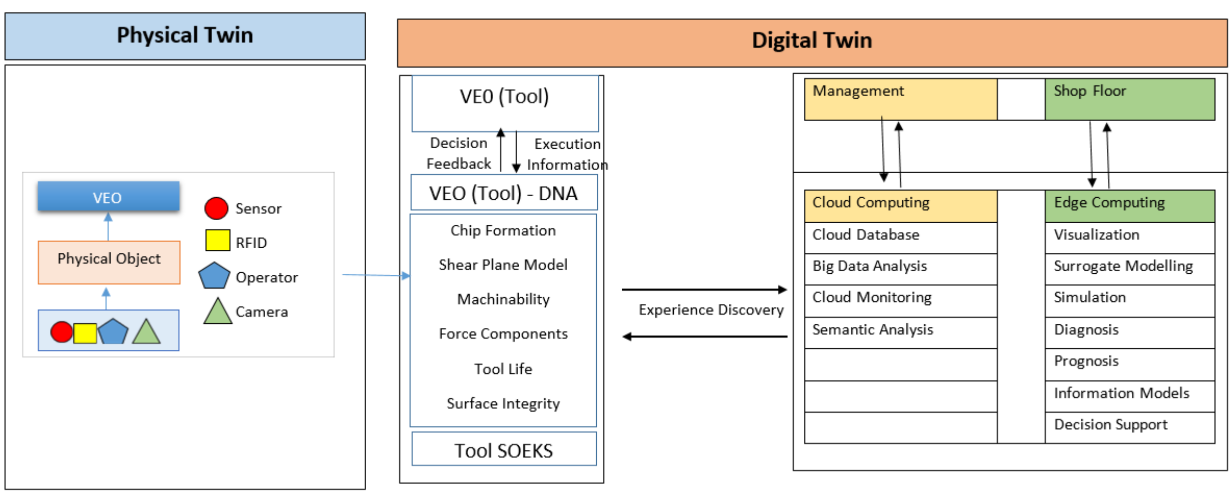

Figure 2: Digital twin implementation for VEO

The proposed architecture works in the following manner. The required data from the VEO setup is captured through sensors, cameras, RFIDs, and test equipment. The acquired data is sorted and stored in the SOEKS format before further processing. This data can be geometrical accuracy, mechanical properties, and signatures for engineering objects like Characteristics, Requirements, Functionality, Connections and Experience, as shown in Figure 2 [9-12]. The concept of DDNA-SOEKS is envisaged on the cloud computing platform [13,14]. The information flow is bi-directional throughout the proposed architecture to enable real-time VEO monitoring and control. The following subsections cover the PT and DT layers' organizational structures, entities, and sub-entities.

3.1. Physical twin

The manufacturing key performance indicators (KPIs) for the PT layer are made up of the VEO experimental setup and sub-entities that help with data collection, such as sensors, parts and test equipment, camera, and device control, and radio frequency identification (RFID) tags.

The sensors might be of two types: (1) connected sensors, such as a high dynamic range (HDR) camera, thermocouple, pyrometer, and voltage/current sensor, or (2) built-in sensors, such as location tracking systems and power measurement for a VEO.

Additionally, in the digital twin implementation for VEO setup, the manufacturing key performance indicators (KPIs) are in charge of carrying out the activities and sending the real-time data to the data collecting and control level entity. Due to this real-time communication, failure detection can be quickly and effectively managed by issuing extra VEO orders.

3.2. Digital twin

Three entities—Data Collection and Control, Semantic Analysis, and User Interface—make up the DT component. The collected data is pre-processed during the data collection (e.g., Tool (SOEKS). Data augmentation, categorization, feature extraction, data cleaning, and data reduction (VEO(Tool)) may be included in this.

Characteristics: Describe the physical characteristics and anticipated advantages of the item that the VEO stands in for. In addition to the geometric dimensions, look, weight, etc., this module will also record any potential concurrent qualities, such as "versatility" or "ease of operation." Characteristics-stored information will aid in better decision-making by providing the answers to questions like, "Which VEO is most suited for a certain physical condition?"

Functionality: By outlining the fundamental ideas and operations of the VEO, functionality is demonstrated. Functionality will retain operational information about an object, such as time expended, its operational bounds, and the process's conclusion. Operation-specific information can be stored, picked out, and reused with the help of this VEO module.

Necessity: By outlining the collection of "necessities" that the VEO needs in order to function precisely. Here, details about the kind and quantity of power the VEO requires, the amount of space needed, and the level of user experience required to operate a VEO will be kept.

Connections: By outlining the connections between the VEO and other VEOs. Many engineering objects interact with one another; these coordinating VEOs may be "parts" of or "necessary for" one another. For the scaling up and creating the interconnection of VEOs in a manufacturing environment, this module of the VEO framework will be crucial.

Current State: The Current State of the VEO; by highlighting the VEO's current parameters. It will provide a response to the issue of whether the VEO is prepared for a specific operation. If the required VEO is occupied, it will forecast when it will be available for the following operation.

Experience: The VEO's experience includes knowledge and information that is dynamic in nature and constantly changes with every new choice, action, or occurrence. In other words, the Experience will have a record of every official decision made in relation to the VEO. Each time a VEO activity occurs, this component of the VEO will also be updated in real-time [10]. Data identification and process control components make up the device control sub-entity. Semantic Analysis, the second entity, analyzes the management and overall operation of DT. Cloud computing environments make up this system. To help portray the OMEs, the computing environment has six primary modules:

(1) Initial visualization (2) Methods of simulation (3) Surrogate models, which are streamlined variations of the procedure that replicate the workings of intricate VEO models, can be utilized to speed up calculation and decision-making. (4) An information model is also used to organize the flow of information further. (5) Diagnosis and prognosis, as well as decision assistance that enables process modification based on simulation and (6) model execution outcomes round out the list.

The user interface, which allows for a variety of interactions between people and systems, is the final item in the suggested hierarchical architecture. The user interface interaction occurs in the cloud. The processed data obtained from computer environments can be used by technicians, shop floor supervisors, operators, designers, planners, and managers in the cloud to deliver control commands.

These commands can modify process parameters like current and voltage for near-optimal part characteristics and process signatures. These include improved geometric accuracy, reduced flaws, reduced surface roughness, and improved mechanical performance.

4. Case Study: Real-time Tool anomaly detection for VEO

To increase process repeatability, part reproducibility, and model interoperability in VEO, the suggested architecture can be used for real-time anomaly detection, as shown in Figure 3.

The Open Platform Communications Unified Architecture is the foundation for communications in this application scenario (OPC UA). It employs the server-client model. The client subscribes while the server gives data content.

Cameras are used to get HDR and thermal images from the experimental setup, while sensors collect temperature, pressure, spindle speed data, etc., from the process. The tensile test and CMM are also used to extract data from VEO parts. The entity responsible for data collection and control receives process and part signatures as well as 1D (such as current and voltage), 2D (such as HDR pictures), and 3D data (e.g., surface roughness). This entity is also given test data, such as the strain-stress curve. These data are collected with regard to the respective components in an information model on a server and are associated with nodes in an address space of OPC UA data.

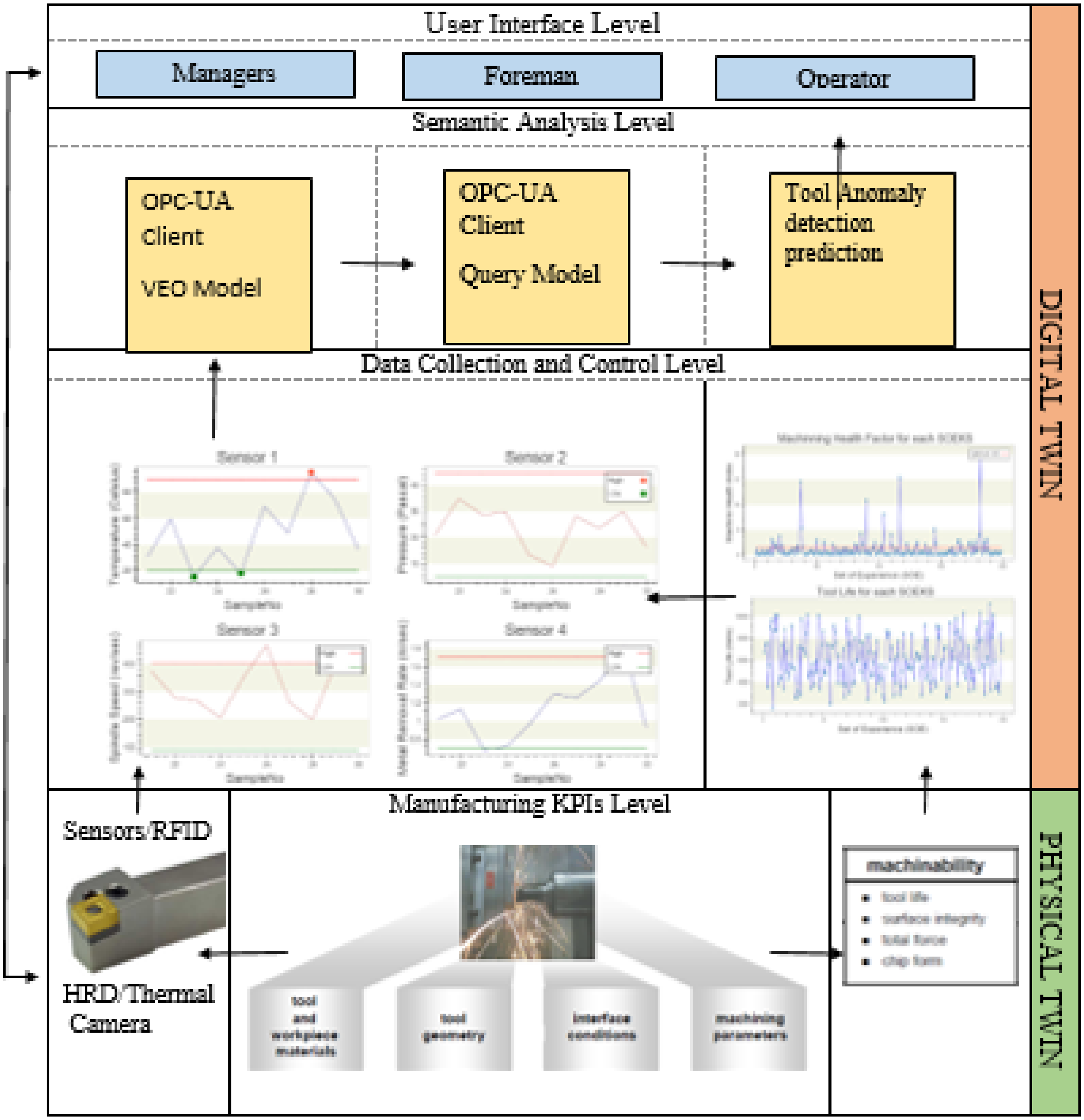

Figure 3: Flowchart of tool anomaly detection and process control in VEO-based DT

Information is constantly being pushed from devices (VEO-Tool), as shown in Figure 3. The model's primary responsibility is to organize and store incoming data efficiently. Streaming data storage is effective in evaluating machine tool performance and maintenance. Any substantial change in the monitored tool's status can be recognized. The change can be characterized as a significant variation in the machine (tool) health value (high and low, as shown in Figure 3), a maintenance procedure, or a shift in the working schedule. These streaming data will be gathered throughout a tool's life cycle and used to create the asset's time machine history. Peer-to-peer asset comparison will take place using this live time tool record. When an asset fails or is replaced, its relative time-machine record shifts from active to historic state and is utilized as a reference for similarity detection and synthesis.

Data from four sensors are collected and organized in the SOEKS format to represent official decisions made while operating the equipment. Calculated similarity to each tool's prior SOEKS is used to compare the current tool behavior. The similarity index is calculated using the Euclidian distance between the variables.

The similarity index obtained for each SOEKS in the repository using the query SOEKS is displayed in Figure 3. The SOEKS with a red dot are those with the most similar SOE. The monitored system's future behavior can be anticipated more precisely once the patterns coincide.

Each set of variables has a specific SOEKS function to calculate the tool life and machine (tool) health index. The matching machine health index and tool life for each SOEKS are shown in Figure 3. To maintain a just-in-time maintenance strategy in the manufacturing plant, it is helpful to forecast the remaining usable life of assets. Additionally, based on the asset's present health status, life projections and historical time machine records can be used to increase asset use efficiency. The data needed to predict potential future usage situations and their effects on the target asset comes from historical usage patterns of similar assets at various health stages. The most effective and productive use pattern for the target asset can be applied in any of those instances.

Since OPC UA is a cross-platform, open-source standard for data exchange, it addresses the interoperability and data sharing concerns of integrating the models and information in many platforms. Real-time anomaly detection is made possible by this standard for real-time communication, which enables open, deterministic, real-time communication between automation systems. It can guarantee data security since it uses client-server communication protected by user authentication and authorization.

5. Conclusion

Digital twin (DT) is an enabling technology that integrates cyber and physical spaces into Cyber Physical Systems (CPS) for the incoming era of Industry 4.0. Based on the idea of the digital Manufacturing DNA, a generalized DT implementation architecture for VEO is suggested in this study. Manufacturers can use DTs for real-time decision-making and control of VEO applications thanks to the implementation design. Additionally, it offers a way to navigate the complicated array of standards, tools, and techniques that can be applied to implementing digital twins. To show how the suggested architecture may be used, a real-time anomaly detection application scenario was also examined. In the next step, the full software/hardware representation of the proposed architecture and its implementation in real life manufacturing environment is intended.

References

1. Kim DB, Witherell P, Lipman R, Feng SC. Streamlining the additive manufacturing digital spectrum: A systems approach. Addit Manuf 2015;5:20–30.
2. Kim DB, Witherell P, Lu Y, Feng S. Toward a digital thread and data package for metals-additive manufacturing. Smart Sustain Manuf Syst 2017;1(1):75.

3. Iso. 23247–1. ISO 23247–1: Automation Systems and Integration - Digital Twin Framework for Manufacturing - Part 1: Overview and general principles. Geneva, Switzerland: International Organization for Standardization; 2021
4. Friederich J, Francis DP, Lazarova-Molnar S, Mohamed N. A framework for data-driven digital twins for smart manufacturing. Comput Ind 2022;136:103586.
5. Qiao F, Liu J, Ma Y. Industrial big-data-driven and CPS-based adaptive production scheduling for smart manufacturing. Int J Prod Res 2021;59 (23):7139–59.
6. Everton SK, Hirsch M, Stravroulakis P, Leach RK, Clare AT. Review of in-situ process monitoring and in-situ metrology for metal additive manufacturing. Mater Des 2016;95:431–45
7. Sanin, C. and E. Szczerbicki. “Decisional DNA and the Smart Knowledge Management System: A Process of Transforming Information into Knowledge.” In Techniques and Tool for the Design and Implemention of Enterprise Information Systems, edited by A. Gunasekaran 149–175. New York, NY, USA: IGI, 2008.
8. Shafiq, S. I., C. Sanin, and E. Szczerbicki. “Set of Experience Knowledge Structure (SOEKS) and Decisional DNA (DDNA): Past, Present and Future.” Cybernetics and Systems 45, no. 2, 2014: 200–215.
9. Shafiq, S. I., C. Sanin, E. Szczerbicki, and C. Toro. “Virtual Engineering Objects (VEO): Designing, Developing and Testing Models.” In System Analysis Approach to the Design,Control and Decision Support, edited by L. Borzecki A. Grzech J. Swiatek and Z. Wilimowska 183–192. Wroclaw, Poland: Wroclaw University of Technology Press, 2014.
10. Shafiq, S. I., C. Sanin, E. Szczerbicki, and C. Toro (2014) “Decisional DNA Based Framework for Representing Virtual Engineering Objects.” In Intelligent Information and Database Systems, edited by N. T. Nguyen B. Attachoo B. Trawiński and K. Somboonviwat 422–431. Springer International Publishing.

11. Shafiq, Syed Imran, C. Sanin, C. Toro, and E. Szczerbicki, "Virtual Engineering Object (VEO): Toward Experience-Based Design and Manufacturing for Industry 4.0," Cybernetics and Systems, vol. 46, pp. 35-50, 2015.
12. Syed Imran Shafiq, Cesar Sanin, Carlos Toro and Edward Szczerbicki (2016) Virtual engineering process (VEP): a knowledge representation approach for building bio-inspired distributed manufacturing DNA, International Journal of Production Research, 54:23, 7129-7142, DOI: 10.1080/00207543.2015.1125545
13. Cesar Sanín, Leonardo Mancilla-Amaya, Zhang Haoxi and Edward Szczerbicki (2012) DECISIONAL DNA: THE CONCEPT AND ITS IMPLEMENTATION PLATFORMS, Cybernetics and Systems, 43:2, 67-80, DOI: 10.1080/01969722.2012.654069
14. Muhammad Bilal Ahmed, Syed Imran Shafiq, Cesar Sanin & Edward Szczerbicki (2019) Towards Experience-Based Smart Product Design for Industry 4.0, Cybernetics and Systems, 50:2, 165-175, DOI: 10.1080/01969722.2019.1565123