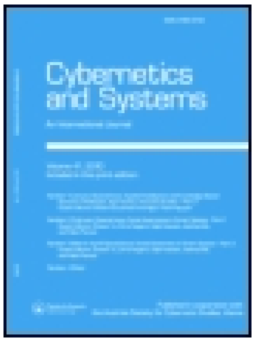

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Manufacturing Data Analysis in Internet of Things/Internet of Data (IoT/IoD) Scenario

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ABSTRACT

Computer integrated manufacturing (CIM) has enormous benefits as it increases the rate of production, reduces errors and production waste, and streamlines manufacturing sub-systems. However, there are some new challenges related to CIM operating in the Internet of Things/Internet of Data (IoT/IoD) scenarios associated with Industry 4.0 and cyber-physical systems. The main challenge is to deal with the massive volume of data flowing between various CIM components functioning in virtual settings of IoT. This paper proposes decisional DNA-based knowledge representation framework to manage the storage, analysis, and processing of data, information, and knowledge of a typical CIM. The framework utilizes the concept of virtual engineering object and virtual engineering process for developing knowledge models of various CIM components such as automatic storage and retrieval systems, automatic guided vehicles, robots, and numerically controlled machines. The proposed model is capable of capturing in real time the manufacturing data, information and knowledge at every stage of production, that is, at the object level, the process level, and at the factory level. The significance of this study is that it will support decision-making by reusing the experience, which will not only help in effective real-time data monitoring and processing, but also make CIM system intelligent and ready to function in the virtual Industry 4.0 environment.

KEYWORDS
Decisional DNA; Internet of data; Internet of things; knowledge representation; virtual engineering objects; virtual engineering process

Introduction

In the modern industrial environment, companies are adopting a higher level of automation and computerization for their production systems to achieve higher efficiency and superior performance. Computer integrated manufacturing (CIM) is one example of such approaches. CIM is defined as the manufacturing approach of using computers to control the entire production process. This integration allows individual processes to exchange data, information, and knowledge with each other and initiate actions. Although manufacturing can be faster and less error-prone by the integration of

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computers, the main advantage is the ability to create automated manufacturing processes. However, there is a substantial challenge for CIM system to have collaborating computational entities, which are in intensive connection with the surrounding world and its ongoing processes, providing and using data-accessing and data processing services available in real time (Nguyen 2005; Baxter et al. 2007). Moreover, there is a need for a mechanism to enhance overall smartness of CIM by extracting knowledge from its raw data and information (Verhagen et al. 2012).

This paper proposes a framework, in which previous knowledge of the CIM along with information communication technology features is utilized to induce intelligence to the CIM system operating in data-intensive environments of Internet of Things (IoT). The proposed model enables micro-level integration of various CIM components, which in turn will not only facilitate the real-time control and monitoring capabilities, but also enhance effective decision-making.

Knowledge Base Concepts for Intelligent Computer Integrated Manufacturing

Computer integrated manufacturing systems do not have any standard knowledge representation yet and like most manufacturing systems lack the capability for data, information and knowledge sharing and exchange (Danilowicz and Nguyen 1988, 2000; Qiu, Chui, and Helander 2008; Duong et al. 2010). In this section, decisional DNA-based techniques of virtual engineering object (VEO) and virtual engineering process (VEP) that are used for developing the knowledge models for CIM are discussed. For the sake of completeness, we briefly introduce our bio-inspired concept of decisional deoxyribonucleic acid (DDNA) first.

Bio-Inspired Decisional DNA

Artificial bio-inspired intelligent techniques and systems play an important role in our effort to bridge the gap between our current society and the one embedded in semantic networks and IoT/IoD. Two of the main challenges of the Semantic Web society are big data handling (Bello-Orgaz, Jung, and Camacho 2016; Nguyen and Jung 2017) and smart storage of information and knowledge in artificial systems, so it can be unified, enhanced, reused, shared, communicated, and distributed between artificial systems (Shadbolt, Hall, and Berners-Lee 2006). Our DDNA concept introduces one of the key components of addressing the above challenge. This concept stems from the role of deoxyribonucleic acid (DNA) in storing and sharing information and knowledge. In nature, DNA contains ”… the genetic instructions used in the development and functioning of all known living organisms. The main

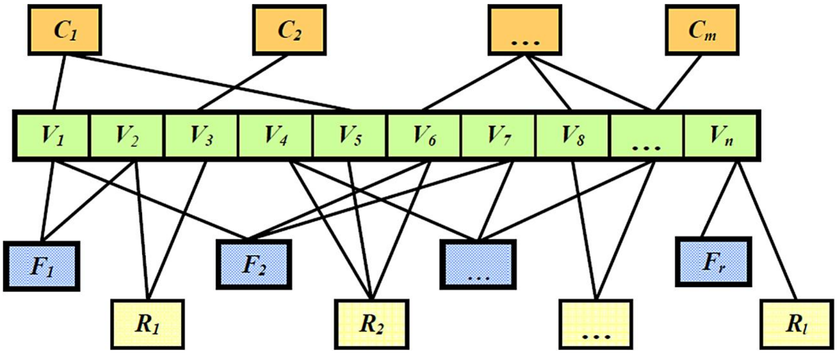

Figure 1. SOE is the combination of four components that characterize decision-making actions (variables V, functions F, constraints C, and rules R) and it comprises a series of mathematical concepts (logical element), together with a set of rules (ruled-based element), and it is built upon a specific event of decision-making (frame element). *Note*: SOE, set of experience.

role of DNA molecules is the long-term storage of information. DNA is often compared to a set of blueprints and the DNA segments that carry this genetic information are called genes" (Sinden 1994). The idea behind our approach was to develop an artificial system, an architecture that would support discovering, adding, storing, improving, and sharing information and knowledge among machines and organizations through experience. We proposed a novel knowledge representation (KR) approach in which experiential knowledge is represented by set of experience (SOE; Figure 1) and is carried into the future by DDNA (Figure 2; Sanín et al. 2009, 2012).

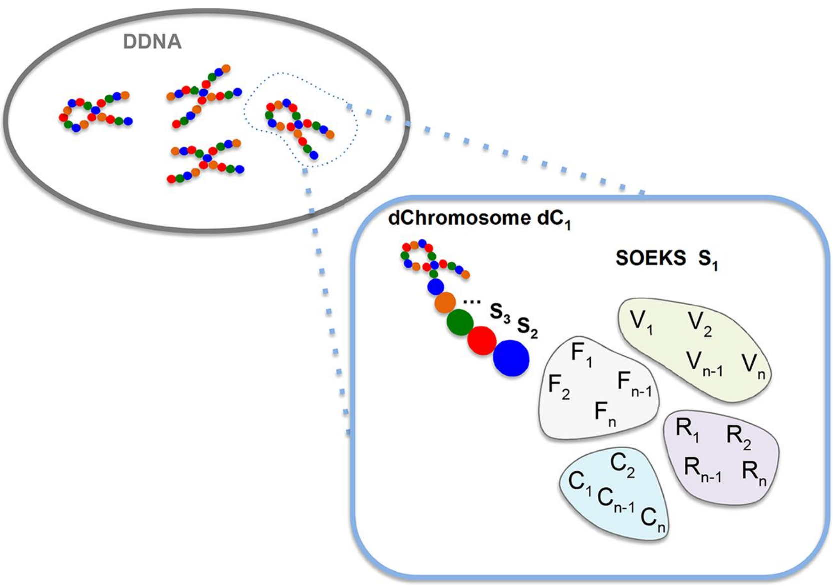

Figure 2. Sets of experience (decisional genes SOEKS) are grouped according to their phenotype, creating decisional chromosomes (dChromosomes), and groups of chromosomes create the decisional DNA (DDNA).

Set of experience and DDNA can be implemented on various platforms (e.g., ontology, reflexive ontology, software-based, fuzzy logic, etc.) in multi-domains, which makes it a universal approach (Zhang, Sanín, and Szczerbicki 2016).

We initially developed the concept and coined the expressions of SOE and DDNA in Sanin and Szczerbicki (2008), Sanín et al. (2009), and Zhang, Sanin, and Szczerbicki (2016). Since then, our research efforts resulted in widespread recognition of this innovative KR technique based on DNA metaphor that is presented as multi-technology shareable knowledge structure for decisional experience with proven security and trust in Sanín et al. (2012), Sanin et al. (2012), Sanchez et al. (2014), and Shafiq, Sanin, et al. (2014b).

Virtual Engineering Object

A VEO is knowledge representation of an engineering artifact. It has three distinct features (Shafiq, Sanin, et al. 2014b; Shafiq, Sanin, et al. 2014a; Shafiq, Sanin, Toro, and Szczerbicki 2015b):

i. the embedding of the decisional model expressed by the SOE,
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 data, information, and knowledge through experience, in a way similar to an expert in that object. A VEO can encapsulate knowledge and experience of all important features related to an engineering object. This is achieved by gathering data and information from six different aspects (chromosomes) of an object viz. characteristics, functionality, requirements, connections, present state, and experience as illustrated in Figure 3.

Virtual engineering object of an engineering object implies that all knowledge and experience related to that object is stored in a structured manner in a repository. This information not only can be used for decision-making regarding its better operational performance, but also can be utilized in areas such as maintainability, serviceability, and reliability of the object. The VEO concept involves the interlinking of the body of knowledge of connected objects, with the aim of constructing subclasses consistent enough for the purposes of the classification scheme.

Virtual engineering object is developed on the notion of cradle-to-grave approach, which means that the contextual information and decision-making regarding an engineering object from its inception until the end of its useful life is stored or linked to it. The knowledge representation technique of set of experience knowledge structure (SOEKS)–DDNA introduced in "Bio-Inspired Decisional DNA" section is used for developing VEO as it provides dynamicity to overcome issues of representing complex data and discrete objects.

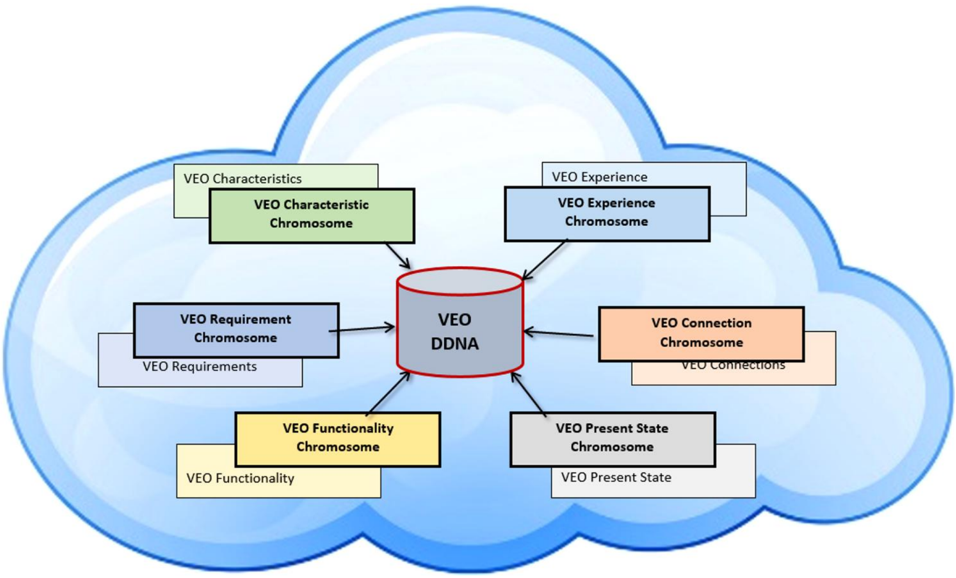

Figure 3. VEO structure (Shafiq, Sanin, Toro, and Szczerbicki 2015b). *Note*: VEO, virtual engineering object.

The changing machining conditions such as, for example, spindle thermal deformation, tool failure, chatter, and work piece deformation induced by clamping force, cutting force, and material inner stress have significant impacts on machining quality and efficiency. Figure 4 in the following section illustrates at the conceptual level of how VEO caters for decision-making problems, which may emerge during the machining process due to complex conditions at this level.

Virtual Engineering Process

In a manufacturing environment, the collection of components/tools/objects constitutes a process. Furthermore, a combination of processes constitutes a system as depicted in Figure 4.

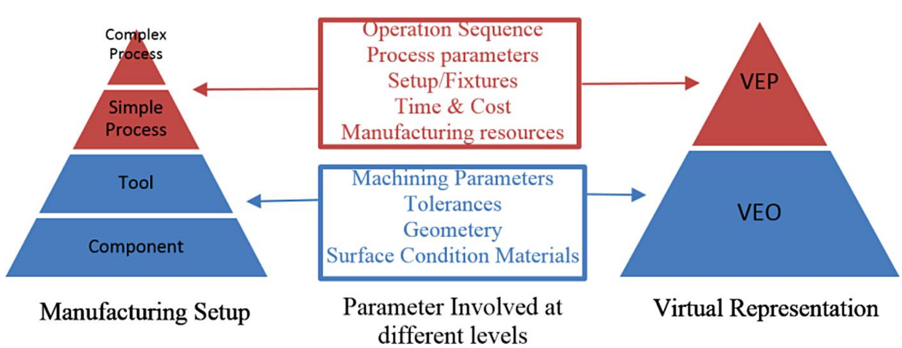

Figure 4. Correlation between physical and virtual world.

Virtual engineering process is a knowledge representation of manufacturing process/process planning of artifact having all shop floor level data and information regarding operations required, their sequence and resources needed to manufacture it as shown in Figure 5. 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, Sanin, Szczerbicki, and Toro 2015a; Shafiq, Sanin, Toro, and Szczerbicki 2015a; Shafiq et al. 2015a).

Process planning is the combination of data and information regarding the operation required, manufacturing sequence, and machines required. In addition to this, for any given VEP information of all the VEOs of the resource associated with the process is also required. Therefore, to encapsulate knowledge of the above-mentioned areas, the VEP is designed (Figure 5) having the following three main elements or modules:

Operations

In this module of VEP, all data and information related to the operations that are required to manufacture an engineering object are stored. This includes knowledge in the form of SOEKS related to operation process and scheduling. Furthermore, functional dependencies between operations are also part of operations. These are subcategorized and their interaction planning functions are given below:

- Scheduling route-based on global and local geometry.
- Processes—process capabilities, process cost.

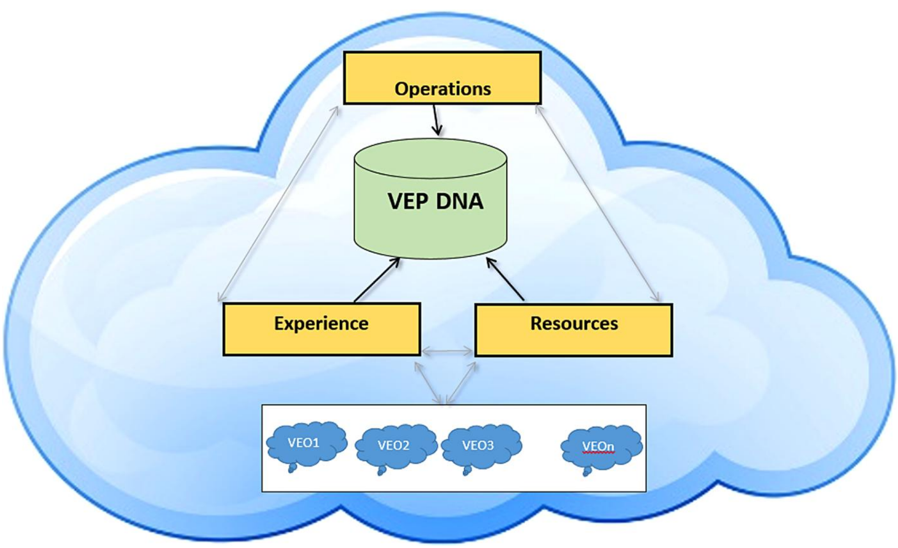

Figure 5. VEP architecture (Shafiq, Sanin, Toro, and Szczerbicki 2015a). *Note*: VEP, virtual engineering process.

- Process parameters—tolerance, surface finish, size, material type, quantity, urgency

Resources

Information based on the past experience about resources used to manufacture a component mentioned in operations module of VEP is stored here. The knowledge of the machine level stored in this section is as follows:

- Machine and tool selections—machine availability, cost machine capability, size, length, cut length, shank length, holder, materials, geometry, roughing, and finishing
- Fixture selection—fixture element function, locating, supporting, clamping surfaces, stability

Furthermore, as discussed in "Virtual Engineering Object" section, the information of VEO categorized under characteristics, requirements, functionality, present state, connections, and experience is also linked with this section.

Experience

In the experience module, links to the SOEKS of VEOs along with VEP having past formal decisions to manufacture engineering components are stored. They represent the links to SOEs based on past experience on that particular machine to perform given operation along with operational and routing parameter.

Salient Features of VEO/VEP

As discussed in the previous section, VEO/VEP works on the knowledge representation technique of SOEKS and decisional DNA. Experimental case studies (Shafiq, Sanin, et al. 2015a) have proven that DDNA-based VEO/VEP knowledge system will have following features:

- Versatility and dynamicity of the knowledge structure, which provides flexibility to change according to the situation.
- Storage of day-to-day explicit experience in a single structure, which makes it ever evolving.
- Transportability, adaptability, and shareability of manufacturing data, information, and knowledge.
- Predicting and decision-making capabilities based on the collected past experience.
- Achieving decisional efficiency, having the right quality and quantity of knowledge at the right time.

Methodology for Developing a Framework for Intelligent CIM

Computer integrated manufacturing system is the computerized control and monitoring of production operation, using manufacturing automation. It incorporates several operations such as manufacturing (machining process), inspection, quality control, assembly, raw material and finished good storage, material handling and transfer systems, radio-frequency identification (RFID) technology for real-time data management and CIMSIM control system for remote monitoring and adjustment.

The CIM system under study has the following components:

- Automatic storage and retrieval system (ASRS)
- Automatic guided vehicle (AGV)
- Transfer conveyer
- RFID tracking system
- Machining operation (CNC-Lathe, CNC-Mill)

A typical CIM process would be as follows: the AGV retrieves the pallet from the ASRS. The pallet can be programmed for specific operation using RFID. The AGV then carries the pallet to specific operations such as machining, assembly, inspection, or storage.

The present study is conducted in four stages as presented in Figure 6. In stage 1 of the study, detailed working, architecture, input and output parameters of CIM components were analyzed. This stage was necessary for stage

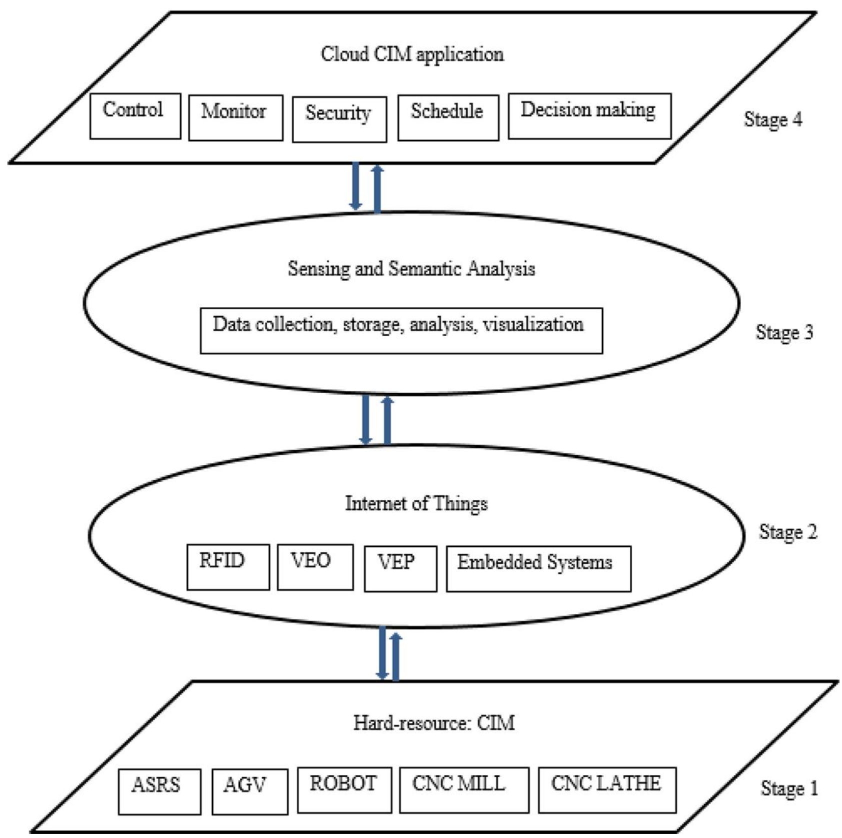

Figure 6. Framework for the intelligent CIM in IoT setting. *Note*: CIM, computer integrated manufacturing; IoT, Internet of Things.

2 where knowledge models of physical components of CIM are developed. These models are interconnected via the Internet and are capable of sending and receiving data and hence forms IoT (Hermann, Pentek, and Otto 2015). In stage 3, real-time semantic analysis and visualization of the captured data are done. And finally, in stage 4, the inferred knowledge from the past experience is utilized in controlling, monitoring, and future decision-making, etc.

Components of Computer Integrated Manufacturing as Knowledge Entities

As discussed in "Virtual Engineering Object" section, VEO is a knowledge representation of engineering artifacts. In this study, each physical component of CIM is considered as a VEO and correspondingly the following knowledge models are developed: ASRS-VEO, AGV-VEO, Robot-VEO, Lathe-VEO, Mill-VEO, and Arm-VEO. Figure 7 illustrates the structure of Lathe-VEO knowledge model having information regarding its characteristic, functionality, requirement, connections, present state, and experience of the Lathe. Furthermore, adhering to the structure of SOEKS–DDNA, for each module

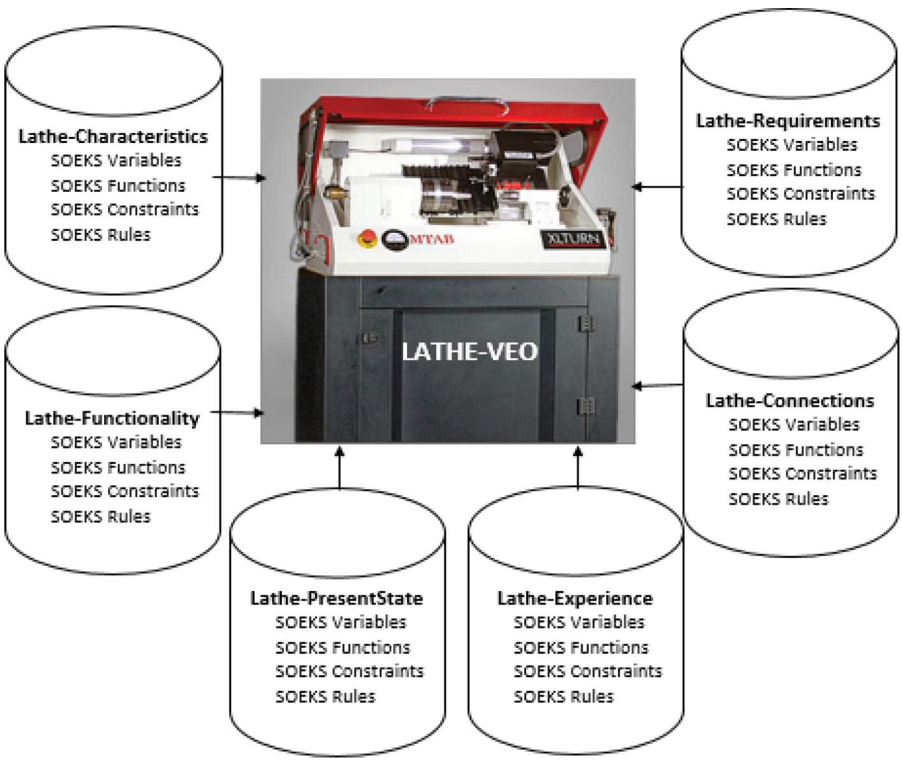

Figure 7. Structure of ASRS-VEO. *Note*: ASRS, automatic storage and retrieval system; VEO, virtual engineering object.

data and information is structured according to variables, function, constant, and rules related to every formal decision. A sample of comma-separated values (CSV) files of experience module of ASRS-VEO, Lathe-VEO, and Mill-VEO are shown in Appendix 1, Appendix 2, and Appendix 3. On the same pattern information of characteristics, requirement, connections, present state, functionality related to ASRS-VEO are gathered.

Similarly, knowledge models for AGV-VEO, Robot-VEO, ASRS-VEO, Mill-VEO, and Arm-VEO are developed as shown in Figure 8.

In a typical CIM setup, the *parts* to be manufactured are indistinguishable. We propose to develop VEP of every *part* that provides a label an identity for each *part* and determines its path through the production process. The VEP information will accompany the *part* to the intended place where it will be used to fulfill its purpose. Appendix 4 shows the sample CSV file having VEP experience module. The *part* is no longer an ambiguous entity and its information can be accessed at any stage of its life cycle. This VEP information can be stored on RFID tag, which helps to keep the *part* in control throughout machining and assembly operations. RFID signals keep track of which parts are completed and ready for shipping. Factory's entire logistics system is also steered by RFID that makes is easier to get the overall picture of the flow of wares and thus reduce the warehouse stock. With the help of VEP and RFID machines and products can increasingly communicate among themselves without people (see stage 2 for Figure 6). This technique makes production a zero defect system, mistakes can be recognized immediately

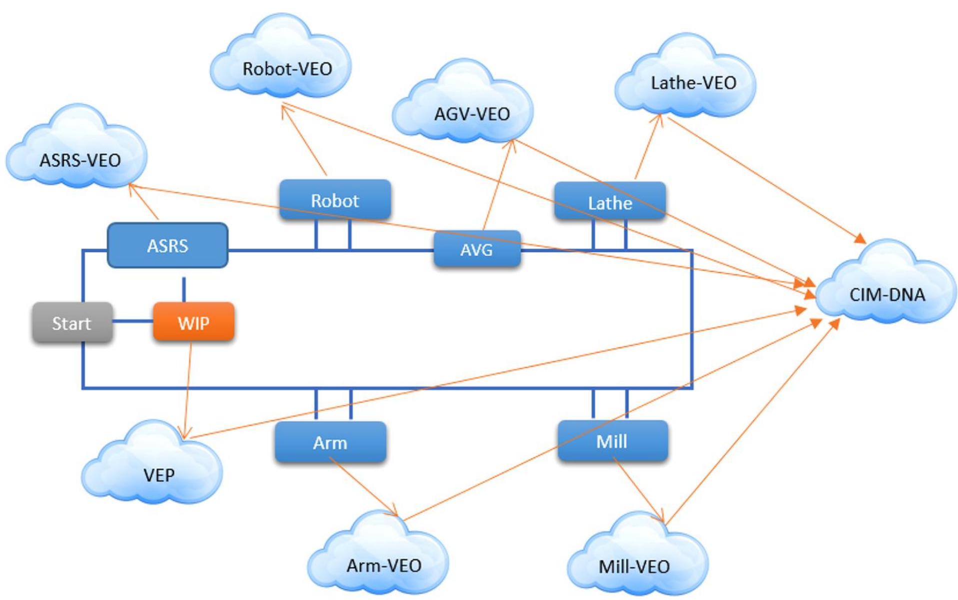

Figure 8. Knowledge representation architecture of CIM. *Note*: CIM, computer integrated manufacturing.

and can be corrected. This is also one of the features of building Industry 4.0 (Posada et al. 2015). Industry 4.0 is the integration and assimilation of a number of smaller concepts such as "Cyber-physical systems (CPS)," "Internet of things (IoT)," "Internet of services (IoS)," "Internet of data (IoD)," "smart products," etc. (Kagermann, Wahlster, and Helbig 2013; Max et al. 2014).

As mentioned before, the architecture of VEO is envisaged on cloud computing; thus, all the *part* data can be accessed on the Internet. Once the product is delivered to the customer and it is used in the manufacturing process, the assembly generated automatic information that can be accessed through the Internet as well, and the manufacturer can monitor parts performance and decided what kind of product can be required in the future. Moreover, digital manufacturing footprints of machine components and products that are produced in a CIM-DNA are also attained as shown in Figure 8.

Extracting Knowledge and Semantic Analysis of Data

Vast amounts of data travel constantly through the factory via VEOs and VEPs. Once the data are collected, it is necessary to prepare it for its exploitation. First of all, there is a necessity of some filtering, as all the raw data are not useful. The outliers and any other fragment of data that is considered noise are eliminated. The next step is to extract knowledge from the collected data, which is achieved by querying the CIM-DNA knowledge repository.

Given a pair of sets of experience *CIM-DNA* (entire CIM repository) and $querySOE_j$ (SOE made up of query) $\in S$, it is possible to generate a similarity metric of the variables called $S_V \in [0,1]$ by calculating the distance measure between each of the pairwise attributes $k \in CIM\text{-}DNA_i$ and $querySOE_j$. The Euclidean distance measure has been selected based on its simplicity and extended use. Besides, a normalization form was included following the notion of the range of comparison, that is, the maximum function. The similarity metric takes the following Eq. (1):

$$S_V\left(CIM\_DNA, querySOE_j\right) = \sum_{k=1}^{n} w_k \left[\frac{\left|CIM\_DNA_{ik}^2 - querySOE_{jk}^2\right|}{\max\left(\left|CIM\_DNA_{ik}\right|, \left|querySOE_{jk}\right|\right)^2}\right]^{0.5}$$
$$\forall k \in CIM\_DNA_i \wedge querySOE_j \tag{1}$$

The parser is written in JAVA programming language to read the information from the CSV files and convert them into SOEKS. Moreover, using formula (1), it calculates the similarity between a query SOEKS and the SOEKS collected in the CIM-DNA knowledge repository.

Results and Discussion

Table 1 gives the sample query that was executed to find the most similar SOEKS. For example, in query 1, VEP similarity is calculated for a product CLY-1 when total time = 12 min, tolerance = −0.1 and finish = 1.8. Figure 9 illustrates the execution of this query. CIM-DNA returns the top most similar SOEKS which, in this particular case, is VEP-Code no 9 having similarity 0.877. The query also returns the codes of ASRS-VEO, Robot-VEO, Lathe-VEO, Arm-VEO, and Mill-VEO for the most similar VEP-Code (Table 1). This enables to fetch all the micro-level details of each component corresponding to most similar VEP-SOEKS.

The approach helps to categorize the past decisions taken on the CIM and then prioritize them according to the situation.

The main contribution of this work is to demonstrate and implement knowledge-based CIM environment in data-intensive Iot/IoD scenario. The CIM-DNA, which is the representation of manufacturing process collective computational intelligence, is created by capturing the experience of engineering objects and engineering processes and then using this information for the construction of VEO and VEP. The SOEKS and DDNA are applied as the

Table 1. Sample query with input variables corresponding output.

Input				Output						
Query	Product code	VEP variables	VEP variable values	Top VEP similarity	VEP code	ASRS-VEO code	Robot VEO code	Lathe VEO code	Arm-VEO code	Mill-VEO code
1	CLY-1	Total Time	12	0.877	VEP9	ASRS14	R4	L3	A6	M3
		Tolerance	−0.01							
		Finish	1.8							

VEP, virtual engineering process; VEO, virtual engineering object.

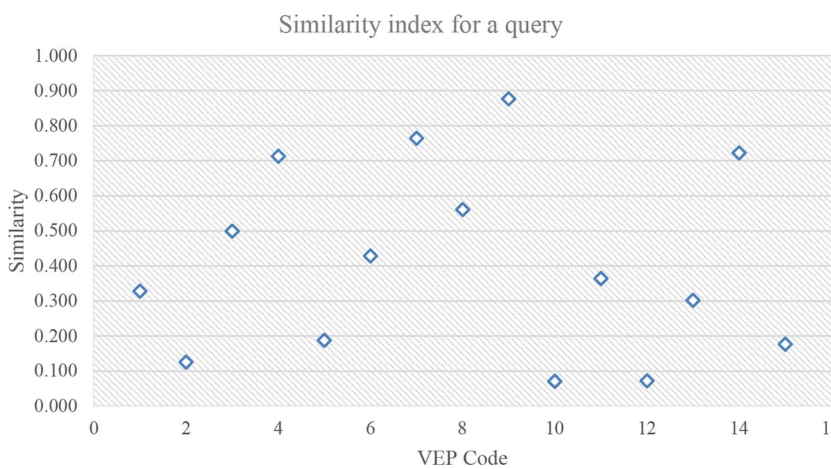

Figure 9. Calculation of similarity for each VEP-SOEKS. *Note*: VEP, virtual engineering process; SOEKS, set of experience knowledge structure.

knowledge representation structure for gathering the experience. Furthermore, VEF–VEP is used as a tool for decision-making processes that can enhance different CIM systems with predicting capabilities and facilitate knowledge engineering processes. Moreover, CIM-DNA readily copes with self-organizing production and control strategies; this is a strong linking instance of product life-cycle management, industrial automation, and semantic technologies as required for cyber-physical systems and Industry 4.0.

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Appendix 1: Experience of ASRS-VEO

ASRS-VEO code	Product code	Pallet position	Next station	Receiving station	Total time
ASRS1	CYL-1	R1C1	Lathe	Milling	13.53
ASRS 2	CYL-1	R1C2	Lathe	Milling	8.70
ASRS 3	CYL-1	R1C3	Lathe	Milling	6.77
ASRS 4	CYL-2	R1C4	Lathe	Milling	9.67
ASRS 5	CYL-2	R1C5	Lathe	Milling	8.70
ASRS 6	RECT-1	R2C1	Lathe	Milling	14.50
ASRS 7	RECT-1	R2C2	Lathe	Milling	13.53
ASRS 8	RECT-2	R2C3	Lathe	Milling	6.77
ASRS 9	RECT-2	R2C4	Lathe	Milling	11.60
ASRS 10	RECT-2	R2C5	Lathe	Milling	8.70
ASRS 11	MISL-1	R3C1	Lathe	Milling	12.57
ASRS 12	MISL-2	R3C2	Lathe	Milling	8.70
ASRS 13	MISL-3	R3C3	Lathe	Milling	14.50
ASRS 14	MISL-4	R3C4	Lathe	Milling	12.57
ASRS 15	MISL-5	R3C5	Lathe	Milling	10.63

Appendix 2: Experience of Lathe-VEO

Lathe-VEO code	Product code	Program code	Feed	Speed	Machining time
L1	CYL-1	L-T-1	0.12	577	5.64
L2	CYL-1	L-T-2	0.07	1199	3.63
L3	CYL-1	L-TT-1	0.10	574	2.82
L4	CYL-2	L-TT-2	0.11	1326	4.03
L5	CYL-2	L-G-1	0.12	1333	3.63
L6	RECT-1	L-T-3	0.08	1371	6.04
L7	RECT-1	L-T-4	0.09	810	5.64
L8	RECT-2	L-TT-3	0.09	661	2.82
L9	RECT-2	L-TT-4	0.10	1103	4.83
L10	RECT-2	L-G-2	0.06	1155	3.63
L11	MISL-1	L-T-5	0.11	1231	5.24
L12	MISL-2	L-T-6	0.11	1388	3.63
L13	MISL-3	L-TT-5	0.09	1282	6.04
L14	MISL-4	L-TT-6	0.10	689	5.24
L15	MISL-5	L-G-3	0.11	1156	4.43

Appendix 3: Experience of Mill-VEO

Mill-VEO code	Product code	Program code	Feed	Speed	Machining time
M1	CYL-1	M-1	0.08	889	4.36
M2	CYL-1	M-2	0.06	1239	2.81
M3	CYL-1	M-3	0.1	896	2.18
M4	CYL-2	M-4	0.11	912	3.12
M5	CYL-2	M-5	0.08	872	2.81
M6	RECT-1	M-6	0.06	1352	4.68
M7	RECT-1	M-7	0.1	1153	4.36
M8	RECT-2	M-8	0.1	926	2.42
M9	RECT-2	M-9	0.12	1295	4.83
M10	RECT-2	M-10	0.07	1284	5.80
M11	MISL-1	M-11	0.12	924	3.38
M12	MISL-2	M-12	0.12	978	7.25
M13	MISL-3	M-13	0.06	1151	5.32
M14	MISL-4	M-14	0.06	1055	7.25
M15	MISL-5	M-15	0.11	812	7.25

Appendix 4: Experience of VEP

VEP code	Product code	Part material	Lathe-VEO code	Mill-VEO code	Total time (min)	Tolerance (mm)	Finish
VEP1	CYL-1	Aluminum	L1	M1	14.53	0.01	1.82
VEP 2	CYL-1	Aluminum	L1	M2	9.7	−0.02	1.82
VEP 3	CYL-1	Aluminum	L1	M3	7.77	−0.03	1.82
VEP 4	CYL-1	Aluminum	L2	M1	10.67	0.00	1.82
VEP 5	CYL-1	Aluminum	L2	M2	9.7	0.01	2.73
VEP 6	CYL-1	Aluminum	L2	M3	15.5	0.00	1.82
VEP 7	CYL-1	Aluminum	L3	M1	14.53	0.01	2.73
VEP 8	CYL-1	Aluminum	L3	M2	7.77	−0.01	2.73
VEP 9	CYL-1	Aluminum	L3	M3	12.6	−0.02	1.82
VEP 10	CYL-1	Mild steel	L1	M1	9.7	0.03	2.73
VEP 11	CYL-1	Mild steel	L1	M2	13.57	0.05	1.82
VEP 12	CYL-1	Mild steel	L1	M3	9.7	−0.03	1.82
VEP 13	CYL-1	Mild steel	L2	M1	15.5	0.01	2.73
VEP 14	CYL-1	Mild steel	L2	M2	13.57	0.04	1.82
VEP 15	CYL-1	Mild steel	L2	M3	11.63	−0.03	1.82