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Knowledge-Based Virtual Modelling and Simulation of Manufacturing Processes for Industry 4.0

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Abstract— **Industry 4.0 aims at providing a digital representation of a production landscape, but the challenges in building, maintaining, optimizing, and evolving digital models in inter-organizational production chains have not been identified yet in a systematic manner. In this paper, various Industry 4.0 research and technical challenges are addressed, and their present scenario is discussed. Moreover, in this article, the novel concept of developing experience based virtual models of engineering entities, process, and the factory is presented. These models of production units, processes, and procedures are accomplished by virtual engineering object (VEO), virtual engineering process (VEP) and virtual engineering factory (VEF), using the knowledge representation technique of Decisional DNA. This blend of the virtual and physical domains permits monitoring of systems and analysis of data to foresee problems before they occur, develop new opportunities, prevent downtime and even plan for the future by using simulations. Furthermore, the proposed virtual**

model concept not only has the capability of Query Processing and Data Integration for Industrial Data but also real-time visualization of data stream processing.

Keywords — **Knowledge Engineering, Decisional DNA, Experience-Based Knowledge Representation, Industry 4.0, Virtual Engineering Objects, Virtual Engineering Processes, Virtual Engineering Factory**

I. INTRODUCTION

Industry 4.0 is the digital industrial transformation emerging from the comprehensive networking and automation of all areas of production. Equipment, machinery, materials, and end products capture environmental conditions and processing status via sensors and communicate with one another via embedded software. Industry 4.0 is based on the concepts and technologies that include: Internet of things (IoT), Internet of services (IoS) and cyber-physical systems (CPS) [1]. It builts on interaction via Internet that permits a continuous collaboration and exchange of information, between humans (C2C), humans and machines (C2M), and between machines (M2M) [2]. The idea of Industry 4.0 allows mass customization at a lower cost, higher quality, and faster processing. It is a vision where smart products, smart equipment, and resources interact autonomously for dynamic optimization. This idea enables companies not only to organize their production process more efficiently but also to manufacture customized products within the given setup at the same cost of manufacturing. New business and production models can also emerge in this way based on the evaluation and utilization of masses of incoming data, for instance, from the provision of optimized maintenance services.

However, for most enterprises, the methodology to adapt and implement Industry 4.0 is not transparent. In this article, a generic Industry 4.0 framework is explained for testing out new technologies and creating a new approach to production.

The structure of this article is as follows. In section 2, critical components of Industry 4.0, as identified in the literature, and their significance and implementation challenges are outlined. In section 3, technical challenges in the implementation of Industry 4.0 are discussed along with the direction of research in this area. Section 4 presents the concept of VEO, VEP, and VEF and its relevance to Industry 4.0 scenario. An experimental framework to implement Industry 4.0 is presented in section 5, in which production data coming out of a machine are monitored and analyzed in real time. Also, in section 5, the results of virtualization and visualization are shown. In the final section, the conclusions drawn from this research are discussed.

II. CRITICAL ELEMENTS OF INDUSTRY 4.0

Industry 4.0 embodies the production automation, and it mainly comprises enabling technologies such as CPS, IoT, and cloud computing [3, 4]. According to German Trade and Invest (GTAI) [5], Industry 4.0 signifies the technological evolution from embedded systems to CPS. Industry 4.0 is a research area of keen interest for industry and the academic world. Many experiments for the application of Industry 4.0 are carried out in a wide range of areas such as health care, smart cities, power system, children keeper service, water distribution systems, fire handling, autonomous vehicle, communication and transportation [6, 7].

In Industry 4.0, the integration of virtual space with the physical world is achieved by embedded systems, semantic machine-to-machine interaction, IoT and CPS technologies; besides, a new generation of industrial systems, such as intelligent factories, is evolving to deal with the intricacy of production in the cyber-physical setting [8]. To achieve the functionality mentioned above, Industry 4.0 involves highly specialized areas of technology. The critical factors and the subfactors of these areas identified in the literature [7] are presented in table 1:

TABLE I

CRITICAL FACTORS AND SUB FACTORS OF INDUSTRY 4.0

Factors	Sub Factors
IoT, IoS and related technologies	RFID, Sensors, Actuators, GPS, etc.
	Connectivity and Networks, WSN, M2M
	Data Exchange
	People and Services
CPS and CPPS	Integration of computational algorithm and physical components
	Smart and Connected Communities (S&CC)
	Virtual Objects
Big Data and Analytics	Volume
	Veracity
	Variety
	Velocity
	Validity
	Volatility
	Cloud Computing
	Visualization
Cyber Security	Application Security
	Information Security
	Network Security
	Disaster Recovery/Continuity Planning
	Operational Security
	End User Security
System Integration	Horizontal Integration
	Vertical Integration
	End-to-end Integration
Other Tools and Techniques	Augmented reality
	Autonomous Robots
	Additive Manufacturing
	Simulation
	Standardization

III. RESEARCH DEMANDS AND DIRECTIONS

Although it is generally acknowledged that Industry 4.0 concepts, ideas, and implementation are at their early stages [9], this new framework creates some significant challenges which need to be addressed quite urgently. These challenges cover a broad spectrum of scientific, technological, and even societal issues [10]. From the technological perspective, we need to address the following key issues and challenges that are briefly characterized in subsections A, B, and C below: technical challenges, standardization, and security and privacy. Research trends which try to address the presented challenges are discussed in subsection D.

A. Technical challenges

The predominant Industry 4.0 related technical challenges can be designated as follows:

1) For the majority of manufacturing companies, their current information and communications technology (ICT) infrastructures do not support horizontal, vertical, and end-to-end integration required by the digital transformation to Industry 4.0 [11]. As suggested by Arnold, Kiel, and Voigt [12] the transition of the conventional industrial setting to the Industry 4.0 systems, the entirely new ICT as well as new business models at all managerial levels need to be developed.

2) Scalability represents another critical issue in the envisaged Industry 4.0 setting. This issue gathers momentum and importance with increasingly more physical objects being connected to the manufacturing networks and processes. These networks will be used for a progressively wider variety of sizable volume transactional data and information at elevated speed, and thus, the quantity of things will unavoidably grow exponentially [13].

3) The importance of data analytics and data science will grow increasingly in the Industry 4.0 environment. With IoT becoming an inherent part of Industry 4.0, a vast number of interconnected things will produce a massive amount of real-time data. These massive amounts of data must be processed to be able to meaningfully enhance manufacturing decision making processes in cyber-physical Industry 4.0 production networks. In order to analyze such quantities of data generated by IoT and new ICT, data science, and data analytics procedures need to be developed and implemented [4]. Implementing practical solutions addressing the above issue and being able to cope with big data from a variety of heterogeneous sources would become of utmost importance and difficulty.

4) IoT-related challenges. IoT is a highly complex heterogeneous network of things connected through several communication technologies [14]. Currently, there is no acknowledged platform which would accommodate the diversity of technologies and applications in such network [15]. Delays in data transformation in IoT networks becomes another critical challenge to be addressed [14]. Further research is needed to challenge the identification and optimization issues at the architectural and protocol levels of IoT [14]. Last, IoT integration with current ICT systems to form a integrated information infrastructure becomes a challenging task that must be addressed to make a smooth transition to Industry 4.0.

B. Standardization

The concept of Industry 4.0 has the capacity of becoming a common global semantic for manufacturing [5]. Industry 4.0 procedures integrate existing technologies with new applications to address the whole spectrum of production related problems. As such, the establishment of a global, uniform production standards is particularly crucial [5, 8]. Developing such a uniform Industry 4.0 related standardization requires a comprehensive large-scale effort from a system-level perspective [16]. A set of consistent technical standards is required to successfully connect different factories and companies into one common network [10]. Researchers have already addressed and reported some standardization attempts concerning IoT and CPS technologies supporting Industry 4.0, showing success at early stages. Among them, the German Electrical and Electronic Manufacturers Association initiated the Reference Architecture Model for Industry 4.0 (RAMI 4.0), a central standard for Industry 4.0. RAMI 4.0 establishes a three-dimensional coordinate system, which identifies all fundamental components of Industry 4.0. With the help of RAMI 4.0, complex unmanageable as a whole system can be divided into subsystems that are easier to control [17].

Another example of Industry 4.0 standardization effort is the initiation by the Industrial Internet Consortium (IIC) of The Industrial Internet Reference Architecture (IIRA) [18]. IIRA defines a standards-based open architecture for Industry 4.0. IIRA intends to develop means to manage interoperability, map technologies, and direct development of standards. IIRA sustains several features related to the standardization. It incorporates a comprehensive set of system types and configurations, a variety of connections in a diverse set of methods, and contextual instances of several types of industries, industry sectors, and applications. Currently, version 1.8 of the IIRA has been made available. This new version was enhanced by adding emerging IoT technologies, concepts, and applications.

The progress of IoT makes Industry 4.0 and IoT standardization even more challenging. Standardization in IoT aspires at enhancing the interoperability of dissimilar systems and applications. The importance of standardization is further urged by the need for understanding and exchanging information coming from different countries [14]. Standards developed for communication protocols, identification purposes, and security and privacy technologies used in IoT will be the critical drivers for the global reach of IoT [14, 19].

C. Information security and privacy protection

Together with progressing the integration of cyber and physical zones, security matters will become increasingly severe in the Industry 4.0 setting, which requires a higher level of privacy protection [8]. The current technology implemented for organizational data and information security will be not sufficient and will not ensure the secure use of new IoT services. Substantial research efforts are needed to tackle the complexities and difficulties of data protection aspects related to IoT deployment, its embedded mobility, and enormous network intricacy [14, 19]. Together with operational IoT, extensive amounts of sensitive personal information would be automatically accumulated and stored. Its protection becomes a much more severe and complicated issue than current security challenges posed by the traditional ICT setting. Because the number of possible attacks routes increase dramatically in IoT settings, any data collected and stored could be jeopardized due to cyber-crime [14, 20]. Typical cases of such crime are identity theft, reputation damage, fake news manipulation, transaction fraud, hacking, etc [14]. Industry 4.0 related cyber-security is still an emerging field of research and application. Much more research needs to be performed to ensure the reliability of IoT and Industry 4.0 protection mechanisms.

D. Research directions

Industry 4.0 evolution will advance incrementally from the existing technologies. To ensure the required pace of this advancement, and to be able to meet the related challenges, strong international research efforts and collaboration is necessary. These research efforts need to consider the following directions:

1) *CPS integration*.

   CPS integration involves combining heterogeneous elements, procedures, and tools. This challenging undertaking comprises developing interfaces to assist heterogeneous modules and their adaptive integration. More research on CPS integration needs to be performed to investigate the possible complexities and uncertainties of interactions between cyber and physical systems [10].

2) *CPS testing and validation*.

   Thorough verification and experimentation are becoming crucial processes for Industry 4.0 implementation. Developing consistent standards and specifications for these processes is an important research undertaking [10].

3) *Blockchain technology*.

   World Economic Forum forecasts that by 2027, 10% of the global Gross Domestic Product will be kept on blockchain-founded technology. Together with its growing popularity, blockchain technology concepts attract considerable interest in the manufacturing sector. Companies began integrating blockchain ideas into manufacturing systems and processes. There are many possible blockchain applications in Industry 4.0. They include scalability, security, resilience and autonomy [21].

4) *Smart devices*.

Envisaged Industry 4.0 production setting is smart, which calls for advanced intelligent devices [10]. Industry 4.0 applies artificial intelligence (AI) procedures and IoT to form intelligent entities and add smartness to systems [14]. Arsénio et al. [22] propose to build the Internet of Intelligent Things by embedding AI into things and networks. It is envisaged that future IoT would have features such as self-configuration, self-optimization, self-protection, and self-healing [7, 14]. Smart objects will evolve further and become even smarter, context-aware, and will have enhanced memory, processing, and reasoning capacities [7].

5) *Resilient smart factory*.

Resilience is the capability of the system to cope with disruption within acceptable degradation parameters [7]. A resilient intelligent factory would consist of structures that are compliant of disruptions and can recover within an acceptable time [5]. Since Industry 4.0 requires the processing of vast amounts of data, smart factories are initiated to deliver data processing reliability and are expected to be resilient. Attaining resilience in Industry 4.0 is a very demanding task. International and interdisciplinary research efforts are needed to further the development of resilient industrial setting, that contributes to the development of a resilient industrial environment. Emerging new technologies such as blockchain are envisaged to add to Industry 4.0 resilience.

6) *The role of present ERP, EIS, ES technologies in Industry 4.0.*

Enterprise Resource Planning (ERP), named sometimes Enterprise Information Systems (EIS) or Enterprise Systems (ES), became dominant software architectures and systems in current industries [7, 23]. Industry 4.0 inspired a discussion on whether these systems will continue to be dominant enterprise software systems [5]. Although GTAI [5] study has not provided a definite conclusion on the matter, it is anticipated that if integrated with Industry 4.0, ERP, EIS, or ES will need to tackle new challenges. As IoT and CPS related technologies make an impact on the new ICT, the future ERP, EIS, or ES will emerge with the new cyber-physical capacities [14].

7) *Industry 4.0's other* bearings.

Industry 4.0 initiates the 4th industrial revolution. It will change all aspects of our lives such as style of work, career paths, education, and so on [11].

IV. VIRTUAL MODELS OF PRODUCTION LANDSCAPE

The idea of VEP and VEO is integrated with Industry 4.0 [24]. In a manufacturing setting, a collection of objects forms a process, and thus the virtual representation of things and processes as VEO and VEP is developed based on the concept of experience-aware knowledge representation Set of Experience Knowledge Structure (SOEKS) or Set of Experience (SOE) for short [25, 26]. The collection of VEPs forms further VEF.

A. *Virtual Engineering Objects (VEO)*

A VEO is a knowledge exemplification of an engineering artefact including experience models, domain, and functionality along with a physical connection to the virtual object in its conception. VEO is formed using cradle-to-grave approach in which data, information, and decision making regarding an engineering item right from its initiation until its actual useful life is linked and stored for future use. A VEO can compress knowledge and experience of every critical feature related to an engineering item. It is accomplished by collecting information from six aspects of an object (as shown in Fig.1.) — Characteristics, Functionality, Requirements, Connections, Present State, and Experience [27, 28].

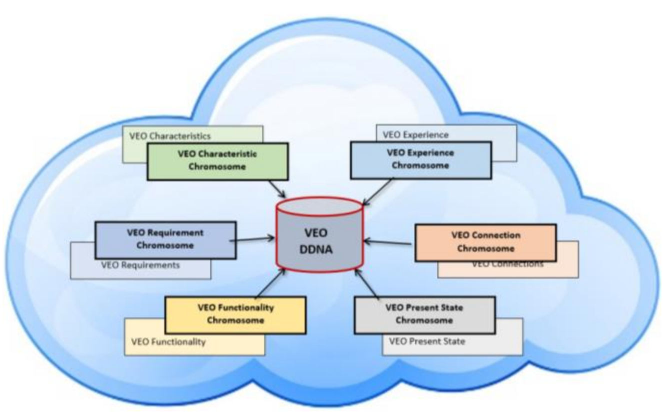

Fig. 1. VEO Architecture

B. *Virtual Engineering Process (VEP)*

Virtual engineering process (VEP) is an experience-based knowledge exemplification of the manufacturing process/process-planning of an engineering item. It includes all relevant shop floor level data and information needed to manufacture the item. VEP deals with the choice of essential production operations and selection of their orders, as well as the determination of resources needed to convert a design concept into the actual physical module. VEP is constructed using and linking the following three modules (i) Operations, (ii) Resources, and (iii) Experience (Fig.2.) [24, 29].

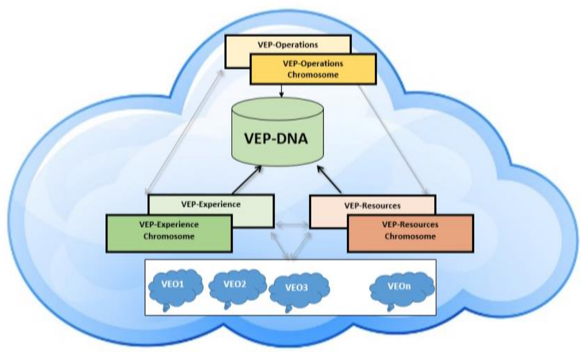

Fig. 2. VEP Architecture

C. *Virtual Engineering Factory (VEF)*

A VEF is an experience-based knowledge exemplification of a factory. It includes information of all combined resources needed to develop the end product by following required operations which begin with inputting raw materials, parts, or set of parts. VEF collects factory experience from the following components (i) VEF Loading/Unloading, (ii) VEF Transportation, (iii) VEF Storage, (iv) VEF Quality Control, and (v) VEF Experience (see Fig.3.) [27].

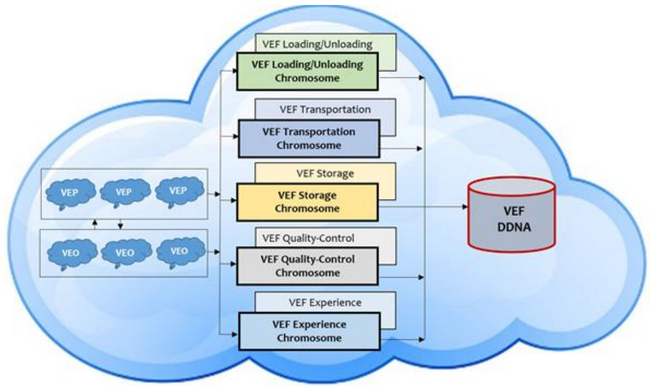

Fig. 3. VEF and its interlinking with VEO and VEP

D. Relevance of VEO_VEP_VEF in CPS founded Industry 4.0

Industry 4.0 merges smart systems, products, machines, products, and procedures to form a complex network. It highlights the idea of constant digitization and networking of all productive elements in a manufacturing organization and creating real-world virtualization into a large information system. In a large CPS setting, a wide amount of models, systems, and concepts from an extensive range of areas play an essential part in determining that structure [30]. We offer to add VEO_VEP_VEF to this perception to support Industry 4.0 as shown in Fig.4.

Careful exploration of VEO_VEP_VEF, CPS and Industry 4.0 reveals that there are major parallels and connections amongst these perceptions at the philosophical as well as at the applied level [24]. These connections are exhibited in Fig.4, showing that in an industrial manufacturing domain Cyber-Physical Production System (CPPS) is actually a specification of CPS at the level of the process. CPPS is a group of CPSs similarly as VEP is of VEOs.

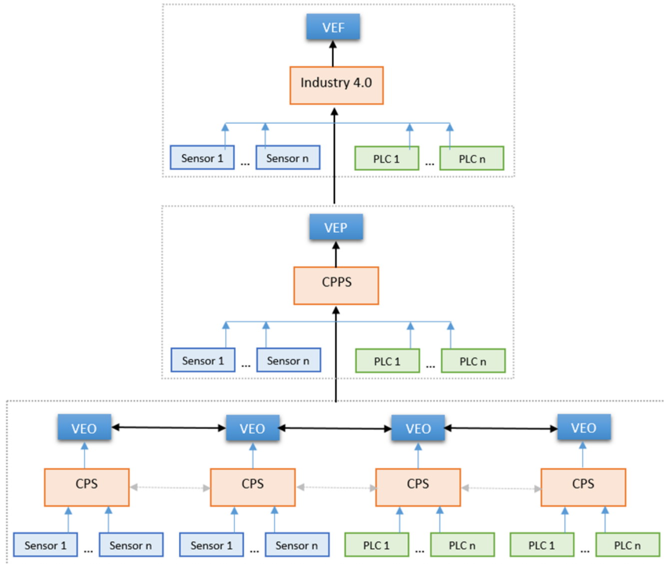

Fig. 4. Role of VEO_VEP_VEF in CPS centred Industry 4.0

The lowest level of Fig. 4 illustrates that VEO offers a knowledge representation for objects associated in the production process, which retains information together with a suitable mode of interaction, and thus VEOs can form CPS. The VEO-VEP is to be implanted in the industrial procedure and can control its logistics and manufacturing workflow (see VEP level in Fig. 4). VEO_VEP_VEF provides suitably compressed information communicated in a customized way providing a case-specific arrangement of cooperation between processes, machines, and parts of machines. This will improve both flexibility and transformability, and thus, support productivity in Industry 4.0.

There are many advantages that VEO_VEP_VEF can offer for Industry 4.0 One of the utmost important features of VEO_VEP_VEF is the self-awareness ability it ensures at every production level. The significance of self-awareness is that it results in enhanced prediction abilities, monitoring, and productivity.

V. Experimental Framework for Industry 4.0

The aims of this framework are to collect data, transform it into SOEKS, form VEO, VEP, and VEF, and perform semantic analysis in real time by means of reusing experience. The challenge is to exploit fabricators own experience for improved decision attaining and to offer real-time smart monitoring system.

For this case study, a production unit consisting of Smart Machine 1 and Smart Machine 2 (see Fig.5.) producing a range of products is considered. SOEKS input and output for VEO, VEP, and VEF in our case study is presented in table 2. First, at the machine/object level, Machine 1 and 2 variables are captured by sensors and sent to Information processing and semantic analysis (IPSA) hub of the production unit. At IPSA, the captured data is standardized in the SOEKS format and transformed into VEO for objects and machines (Fig.5).

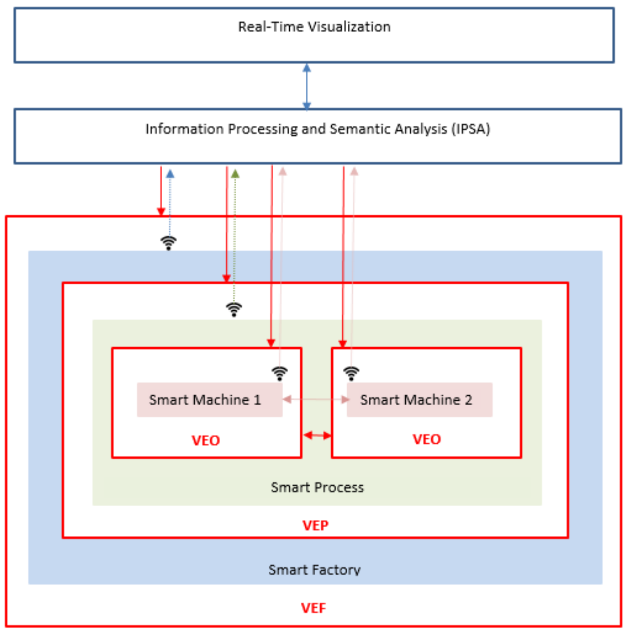

Fig. 5. Case study framework

Next, at the process level, the captured information is transmitted to IPSA and converted into VEP. Eventually, the VEF of a smart production unit is the combination of Factory level information (VEF Input Variables in table 2) with VEPs and VEOs.

TABLE 2

SOEKS INPUT AND OUTPUT VARIABLES AT EACH MANUFACTURING LEVEL

Virtual Model	Input SOEKS Variables	SOEKS Output
VEO	Depth_of_Cut (mm)	Tool_Life (min)
	Cutting_Velocity (rpm)	
	Feed (mm)	
VEP	Machining_Time (min)	Setup_Time (min)
	Idle_Time (min)	Surface_Finish
VEF	Operating_Time (min)	Accepted_Pieces
	Total_Pieces	Rejected_Pieces

As already mentioned, the data captured from the input variables of VEO, VEP, and VEF in the CSV format goes to IPSA, where it is transformed into SOEKS variables. Also, at IPSA, the resultant SOEKS functions are calculated. As shown in table 2, in the presented case study, VEO level SOEKS variables are *Depth_of_Cut*, *Feed*, and *Cutting_Velocity*, and SOEKS function is *Tool_Life*. Similarly, table 2 shows SOEKS variables and SOEKS functions for VEP and VEF delineated and calculated in IPSA. Therefore, rows in table 2 represent experience captured at each level, i.e. VEO-Exp, VEP-Exp, and VEF-Exp. Collection of entire VEF-Exp forms *vefDNA* in the same way as a collection of SOEKS forms Decisional DNA [32]. Similarly, the collection of VEF-Exp and VEO-Exp forms *vepDNA* and *veoDNA*, respectively.

The other qualities of the proposed outline is the ability to perform semantic analysis such as similarity and phenotype computation.

A. Similarity computation

For a pair of SOEKS, $vefDNA_i$ (total VEF repository) and $querySOE_j$ (SOEKS made up of query) $\in S$, it is workable to create a similarity metric of the variables $S_V \in [0,1]$ by determining the distance among each of the pairwise characteristics $k \in vefDNA_i$ and $querySOE_j$. Because of the simplicity and widespread use, the Euclidean space measure is selected. The equation for the similarity metric is shown below:

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

In (1) $vefDNA_{ik}$, $querySOE_{jk}$ are the k^{th} attribute of the sets $vefDNA_i$ and $querySOE_j$, w_k is the weight assigned to the k^{th} attribute, in this case, variable; and n is the amount of variables on $vefDNA_i$.

B. Phenotype computation

SOEKS includes a number of connected components emulating a gene. A SOE can be adapted to a gene, and thus it forms a *phenotype*, which in this case is a merit (value) of a decision in terms of its objective functions. This value of decision is the result of MOO (multi-objective optimization processes) and is called the *efficiency* of the SOE. The *efficiency* or *phenotype value* is a amalgamation of the effective values of the variables and the objective functions. SOEKS retains in its prescribed functions weight values (w) for each of them. Mathematically efficiency estimation is computed as:

$$Phenotype\ of\ the\ SOE\ E_i = \sum_{j=1}^{n} w_{Fi}.F_{ij}(V_i) \tag{2}$$

In (2) w_{Fi} is the weight linked with function F_{ij}. Variables and phenotypes of the SOEKS can be organized and categorized to mine them. Subsequently, interesting relationships and results from the variables and the phenotypes can be obtained, forming a way of discovering new knowledge.

The presented outline also offers the ability to query VEO_VEP_VEF depository and to find the most similar experience at a required level. A sample query is as follows:

querySOE = (Product =B, Operating_Time = 500, Total_Pieces = 20,000, Accepted_Pieces = 1500)

The most similar SOE which matches the query is determined. It specifies the code of the analogous VEF-SOE along with its similarity measure with the query-SOE, along with the VEP code for the above most similar VEF-SOE, and all the connected VEOs.

VI. Results and Discussion

In the VEO_VEP_VEF outline, the linkage between stages is from top to bottom. VEF has linkages with VEP and VEO. Similarly, VEP has linkages of all VEOs. Similarity-identification calculation can be done by two methods. First is to use the combined experience at each stage for the given production unit. The other approach is to detect the most similar experience exclusively at each stage, and then by amalgamating the similarity-identification through phenotyping produce an original virtual experience for the whole factory. For the presented experimental study, the likely query structures, the stages through which it can be performed, and the structure of solutions are shown in table 3. In this table, *Query1* includes VEF variables, but since VEF consists of VEPs and VEOs, thus *Result1* illustrates experience for factory level, which includes VEF-Exp, VEP-Exp and VEO-Exp. In a similar manner, Table 3 provides the structure of *Query2* with the matching *Result2* including VEP-Exp’ and VEO-Exp’, and *Query 3* with its *Result3* consisting of VEO-Exp’’.

TABLE 3

STRUCTURE OF QUERY AND OUTCOME

Sample Query	Query level	Result	Test Query
Query1 = (Operating_Time Total_Pieces, Good_Pieces)	VEO_VEP_VEF	Result1 = VEF-Exp, VEP-Exp, VEO-Exp	[(Operating_Time = 500, Total_Pieces = 20,000, Accepted_Pieces = 1500), (Machining_Time = 30, Idle_Time = 60), (Depth_of_Cut = 60, Cutting_Velocity = 400, Feed = 0.5)]
Query2 = (Cutting_Velocity, Idle_Time)	VEP_VEO	Result2 = VEP-Exp’, VEO-Exp’	
Query3 = (Depth_of_Cut, Cutting_Velocity, Feed)	VEO	Result3 = VEO-Exp’’	

Table 4 shows the means to attain a result with respect to a given query for possible three cases:

1. If factory level experience has the uppermost importance, then VEF-SOEKS variables are queried through *Query1*. Even though only VEF variables are queried, the result will include VEF-Exp along with linked VEP-Exp and VEO-Exp as they are connected from top to bottom. Fig. 6 shows the similarity computation between *Query1* and VEF. It exemplifies that most alike factory level experience is VEF-Exp =1 with the linked process stage experience VEP-Exp = 17, together with object experience VEO-Exp = 15 (table 4, row 1). No phenotyping is there in this case, as there is only single experience at each stage. Thus VEF-Exp = 1, VEP-Exp = 17 and VEO_Exp = 15 is the final result (table 4).

2. If the process level experience has the greatest importance, first VEF-Exp will be attained by performing *Query1* with the result as above (i.e., VEF-Exp =1, VEP-Exp =17, VEO-Exp =15). Since the precedence is for the process, *Query2* queries the VEP stage. Similarity computation between *Query2* and VEP is presented in Fig. 7. The figure shows that the most similar process experience is VEP-Exp'=11 with the linked object level experience VEO-Exp' = 8. So the potential outcomes can be the amalgamation of the results of *Query1* and *Query2* (table 3). Here the phenotyping aspect of Decisional DNA is applied to attain the best SOE from the collection of results found by *Query1* and *Query2*. So, phenotype computation can be found between VEP-Exp=17, VEP-Exp' =11 for VEP, and VEO-Exp =15, VEO-Exp' = 8 for VEO (row two in table 4). Thus outcome is VEF-Exp = 1, VEP-Exp = 11 and VEO-Exp = 8 (table 4).

3. If the object level has the highest importance, VEF-Exp and VEP-Exp can be determined as explained for the above two cases. For VEO there are three dissimilar SOEs; first two (VEO-Exp and VEO-Exp') are achieved from *Query1* and *Query2*. The third SOE (VEO-Exp'') is acquired by executing *Query3* (Fig. 8) Phenotyping takes place between VEO-Exp =15, VEO-Exp'= 8 and VEO-Exp'' = 1. As the VEO has the highest importance, thus the final outcome after phenotype computation is VEF-Exp = 1, VEP-Exp = 17, VEO = 3 (table 4, row 3).

TABLE 4

MECHANISM OF QUERY EXECUTION

Priority	Query Type	Possible Results	Phenotyping (~)	Final Result
VEF	Query1	VEF-Exp=1, VEP-Exp=17, VEO-Exp=15	No	VEF-Exp =1, VEP-Exp = 17, VEO-Exp = 15
VEP	Query1 Query2	VEF-Exp=1, VEP-Exp=17, VEO-Exp=15 VEF-Exp=1, VEP-Exp'=11, VEO-Exp=15 VEF-Exp=1, VEP-Exp=17, VEO-Exp'=8 VEF-Exp=1, VEP-Exp'=11, VEO-Exp'=8	(VEP- Exp=17) ~ (VEP- Exp'=11) (VEO- Exp=15) ~ (VEO- Exp'=8)	VEF-Exp =1, VEP-Exp =11, VEO-Exp = 8
VEO	Query1 Query2 Query3	VEF-Exp=1, VEP-Exp=17, VEO-Exp=15 VEF-Exp=1, VEP-Exp'=11, VEO-Exp=15 VEF-Exp=1, VEP-Exp=17, VEO-Exp'=8 VEF-Exp=1, VEP-Exp'=11, VEO-Exp'=8 VEF-Exp=1, VEP-Exp'=11,	(VEP- Exp=17) ~ (VEP- Exp'=11) (VEO- Exp=15) ~(VEO- Exp'=8)~(VE O-Exp''=1)	VEF-Exp = 1, VEP-Exp = 17, VEO-Exp = 3

VEO-Exp'=3
VEF-Exp=1,
VEP-Exp=17,
VEO-Exp'=3

In this way collective computational intelligence for the given manufacturing process is formed by reusing the experience of engineering objects, processes and factory.

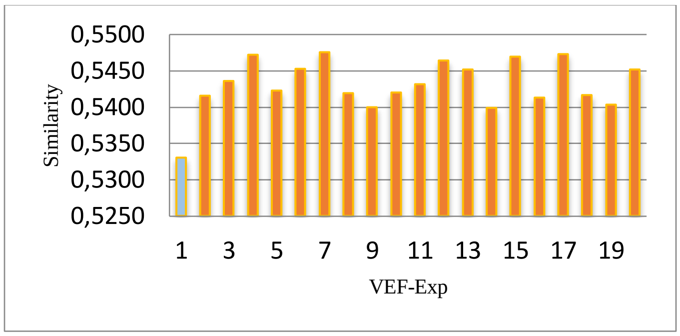

Fig. 6. Similarity Calculation for Query1

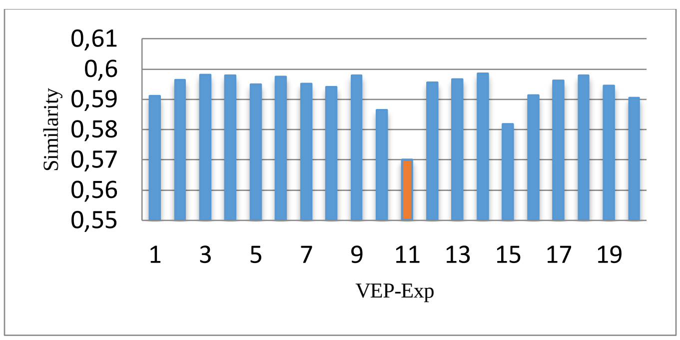

Fig. 7. Similarity Calculation for Query2

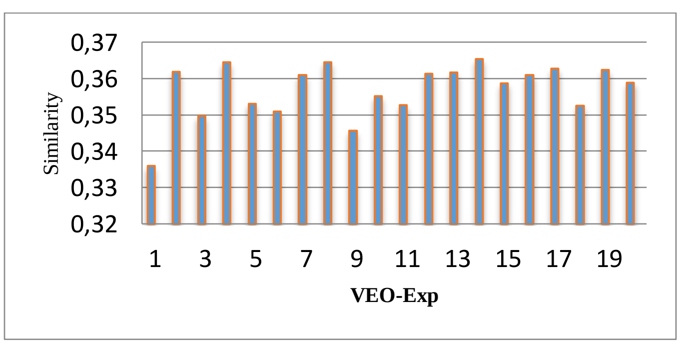

Fig. 8. Similarity Calculation for Query3

The advantage of appluing this methodology is that the two categories of outcomes can be achieved. First, the collective experience with the highest similarity that occurred at each stage of VEF, VEP, and VEO is identified. Secondly, each manufacturing stage can be considered as an autonomous segment for which the best matching past experience can be selected and applied. These autonomous SOEs are merged to create a new virtual experience through phenotyping. Therefore, providing more choices to the management for enhanced decision making.

VII. Conclusions

This paper, after identifying and discussing some critical factors and research challenges related to Industry 4.0, presents a novel general-purpose Industry 4.0 framework which provides the mechanism for the comprehensive real-time capture of data at object, process and factory levels. An experimental case study is presented based on the proposed framework, in which machine data is acquired, analyzed, and visualized in real time. Also, virtual copies of engineering objects, process, and factory in the form of VEO, VEP, and VEP are developed. By applying the proposed framework, the captured data can be searched, correlated, and visualized, which helps engineers discovering hidden trends and patterns. The quality teams can pinpoint variances that require further investigation and identify where problems occur during a process. As the proposed approach has complete traceability right down to the specific parts and their serial numbers, the root cause of any anomalies can be tracked down. In the future, expanding the ideas of the presented proposal beyond the manufacturing domain carries the promise of developing the entire product life cycle model flexible enough for adapting the dynamic industrial changes coming with Industry 4.0.

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