Virtual Engineering Factory: Creating experience base for Industry 4.0

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In recent times traditional manufacturing is upgrading and adopting Industry 4.0, which supports computerization of manufacturing by round the clock connection and communication of engineering objects. Consequently, Decisional DNA based knowledge representation of manufacturing objects, processes and system is achieved by virtual engineering object (VEO), virtual engineering process (VEP) and virtual engineering factory (VEF) respectively. In this paper assimilation of VEO-VEP-VEF concept in the Cyber-physical system based Industry 4.0 is proposed. The planned concept is implemented on a case-study. Also, Decisional DNA features like similarity-identification and phenotyping are explored for validation. It is concluded that this approach can support Industry 4.0 and can facilitate in real-time critical, creative and effective decision making.

Keywords: Cyber-physical system (CPS), Industry 4.0, Decisional DNA, Virtual engineering object (VEO), Virtual engineering process (VEP), Virtual engineering factory (VEF).

Introduction

Unprecedented advancement in the field of information and communication technologies (ICT) has lured manufacturers to utilize its features like managing real-time big data, communication, visualization etc. for enhanced worry free productivity (Posada et al. 2015, Masood et al. 2014).

This idea leads to the emergence of the new concept of Industry 4.0. It is a powerful concept which promotes the computerization of traditional manufacturing plants and their eco-systems towards a connected and 24/7 available resources handling scheme. The goal is an intelligent factory characterized by adaptability, resource efficiency and ergonomics as well as the integration of customers and business partners in business and value processes. Industry 4.0 promotes vision of smart factories and is based on the technological concepts of Cyber-Physical Systems (CPS) and Internet of Things (IoT)(Hermann, Pentek, and Otto 2015, Böhler 2012). CPSs refer to the next generation of engineering systems that require tight integration of computing, communication and control technologies to achieve stability, performance, reliability, robustness and efficiency in dealing with physical systems of many application domains (Lee 2008, Kyoung-Dae and Kumar 2012).

Knowledge engineering plays an important role in the Cyber-physical systems as there is a need for a unified framework to represent the myriad types of data and application contexts in different physical domains and interpret them under the appropriate context (Lui Sha , Lee and Seshia 2014). The concept of Virtual engineering object (VEO), Virtual engineering process (VEP) and Virtual engineering factory (VEF) is experienced based knowledge representation of engineering objects, processes and factory respectively (Shafiq et al. 2013, Shafiq, Sanin, and Szczerbicki 2014, Shafiq et al. 2014a, b, c, Szczerbicki, Sanin, and Shafiq 2015, Shafiq, Sanin, et al. 2015b, a, Shafiq, Sanin, Toro, et al. 2015). This concept is successfully developed and implemented already (Shafiq et al. (in press), Shafiq, Sanin, et al. 2015a). Also, it is established that VEO/VEP/VEF can be treated as a specialized form of the CPS and consequently can be utilized in designing Industry 4.0 (Shafiq, Sanin, et al. 2015a, Shafiq, Sanin, Toro, et al. 2015).

In this work, the concept of virtual manufacturing having three broad levels of VEO, VEP and VEF is deliberated (Shafiq et al. 2013, Shafiq, Sanin, and Szczerbicki 2014, Shafiq et al. 2014a, b, c, Szczerbicki, Sanin, and Shafiq 2015, Shafiq, Sanin, et al. 2015b, a, Shafiq, Sanin, Toro, et al. 2015). This article also focuses on the relevance of VEO-VEP-VEF concept in the CPS based Industry 4.0 by proposing a framework for an intelligent factory. Finally, semantic capabilities such as similarity-identification and phenotype are demonstrated in a test case scenario.

The structure of this paper is as follows: section 2 gives an overview and the central idea of the proposed work. Furthermore, it deals with the basic concept, architecture and objectives of VEO, VEP and VEF. Section 3 discusses the role of the proposed concept in the Industry 4.0 scenario. In section 4, a case study is presented to demonstrate implementation of the planned concept and methodology to extract experience and to reuse it for decision making. Finally, section 5 outlines the potential benefits of this work and conclusions are presented.

VEO/VEP/VEF: Creating manufacturing footprints.

The central idea of this work is to replicate the knowledge and experience of the manufacturing factory and to represent it virtually. Figure 1 illustrates that the physical manufacturing scenario can be classified into three levels which are resources, process and factory; a factory performs various processes; a process in turn uses different resources for its manufacturing. Thus for the complete knowledge representation of a manufacturing system it is categorised into three levels; first is the virtual engineering object (VEO), second is the virtual engineering process (VEP) level and third is the virtual engineering factory (VEF) level. Knowledge representation of these levels is developed both at the individual level and in conjunction with each other. In other words, VEO-VEP-VEF is a mechanism to store and reuse experience related with objects, processes and factory working. Virtual/knowledge representation of engineering objects, processes and system will be beneficial in asset, machine and entire system management respectively. In addition effective decisions can made based on these intelligent virtual manufacturing levels.

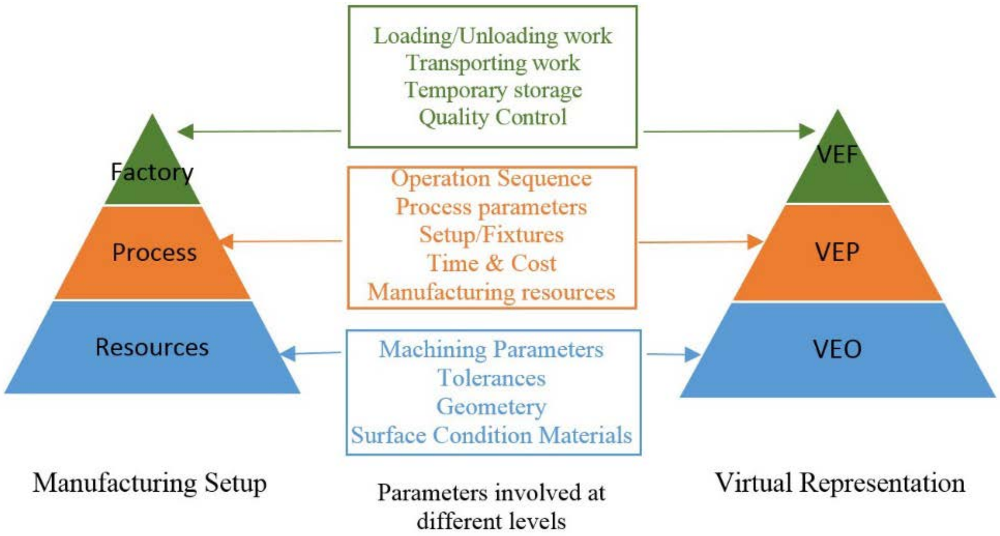

FIGURE 1 Correlation of physical and the virtual world

The three levels of virtual manufacturing are depicted in figure 1. The bottom level is VEO, which is the representation at the individual object/resource/artefact level and is capable of representing all the information at machine level like machining parameters, tolerances, surface conditions etc. The middle level VEP deals with the information at the process or shop floor level like operation sequences, process parameters, time, cost etc. Finally the top level is VEF, it stores the experience/formal decisions related with the various different aspects involved at the system level like material handling, storage quality control, transportation etc.

The powerful knowledge representation technique of Set of experience knowledge structure (SOEKS) and Decisional DNA (DDNA) is used as the technological base for VEO-VEP-VEF. SOEKS-DDNA (Sanin et al. 2012, Sanín et al. 2009, Sanín et al. 2012) is a unique and single structure for capturing, storing, improving and reusing decisional experience. Its 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) built after 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. Thus, the aim of this research is to utilize Decisional DNA to develop manufacturing fingerprint or manufacturing DNA of a factory.

As mentioned above, VEO, VEP and VEF concepts are already developed, implemented and tested. Moreover, it is established that VEO-VEP-VEF has capabilities to enhance performance of not only the traditional manufacturing but also can be significantly important to Industry 4.0 scenario. Before discussing role of VEO-VEP-VEF in Industry 4.0, a brief discussion on these concepts is presented.

A VEO is a knowledge representation of an engineering artefact comprising experience models, domain and functionality along with a physical attachment to the virtual object in its conceptualization. A VEO can encapsulate knowledge and experience of every important feature related with an engineering object. This can be achieved by gathering information from six different aspects of an object viz. (i) Characteristics (ii) Functionality (iii) Requirements (iv) Connections (v) Present State (vi) Experience (Shafiq et al. 2013, Shafiq, Sanin, and Szczerbicki 2014, Shafiq et al. 2014a, b, c, Szczerbicki, Sanin, and Shafiq 2015).

Virtual engineering process (VEP) is a knowledge representation of manufacturing process/process-planning of artefact having all shop floor level information regarding required operations; their sequence and resources needed to manufacture it. To encapsulate knowledge of the above mentioned areas, the VEP is designed having the following three main elements or modules (i) Operations, (ii)

Resources, and (iii) Experience (Shafiq, Sanin, et al. 2015b, a, Shafiq, Sanin, Toro, et al. 2015).

A VEF is a knowledge representation of a manufacturing factory by collection of experience of integrated equipment and human resources, whose function is to perform one or more processing and/or assembly operations on a starting raw material, part, or set of parts. Different modules from which VEF gathers factory experience are (i) Loading/Unloading (ii) Transportation (iii) Storage (iv) Quality-Control (v) Experience (Shafiq et al. (in press)).

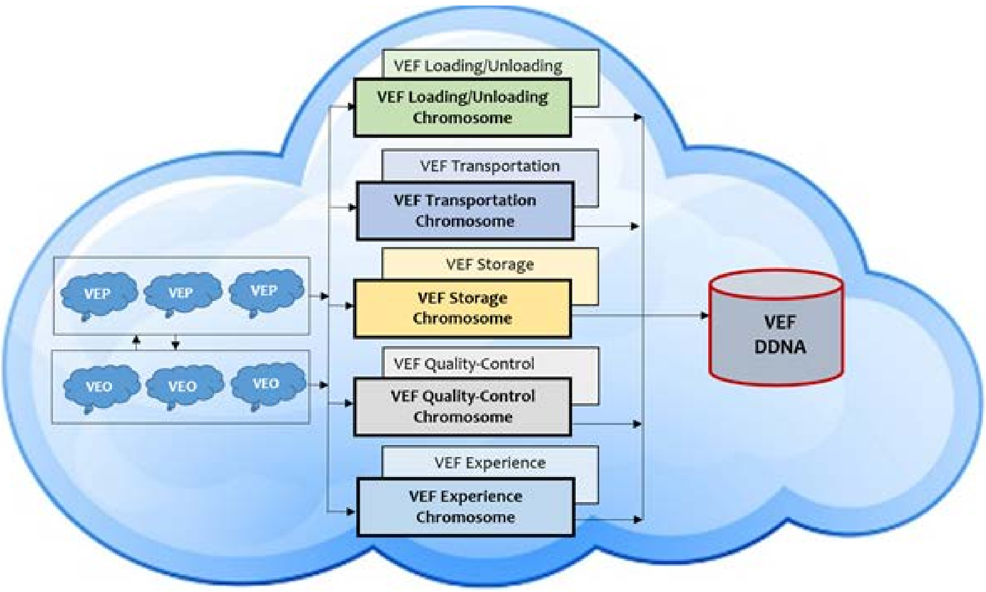

FIGURE 2 VEF Structure intergerating VEP and VEO(Shafiq et al. (in press))

Each factory level experience (i.e. VEF-SOEKS) is associated with a process experience of component (VEP-SOEKS) to be manufactured and that experience of component in turn is linked with objects experience (VEO-SEOKS) for its manufacturing. Based on this idea the architecture of VEF along with mechanism to encompass VEO and VEP within VEF is demonstrated in figure 2. Thus *VEF-DDNA* is created by collecting, connecting and linking VEF, VEP and VEO.

VEO/VEP/VEF relevance in Cyber Physical System based Industry 4.0

Industry 4.0 is combining of intelligent machines, systems, production and processes to form a sophisticated network. It emphasizes the idea of consistent digitization and linking of all productive units in a manufacturing set-up and creating real world virtualization into a huge information system. Industry 4.0 has to be an integration and assimilation of smaller concepts such as the “Cyber-physical systems (CPS)”,"Internet of things (IoT)", “Internet of services (IoS)”, “smart products” etc (Henning Kagermann 2013). In a broad CPS environment, a large number of models, systems and concepts from an extremely wide range of domains play an important part in shaping that structure (Henning Kagermann 2013, Evans and Annunziata 2012, Lee and Seshia 2014). We propose to add VEO-VEP-VEF to this vision that will facilitate and open new manufacturing solutions and services (see figure 3).

Analysis of Industry 4.0, CPS and VEO-VEP-VEF reveals that there are fundamental similarities amongst these concepts both at philosophical as well as practical level (Shafiq, Sanin, et al. 2015a). These connections are displayed in figure 3. The figure shows that in industrial manufacturing domain CPPS is another specification of CPS at the level of process. CPPS is a collection of CPSs in a similar fashion as VEP is of VEOs.

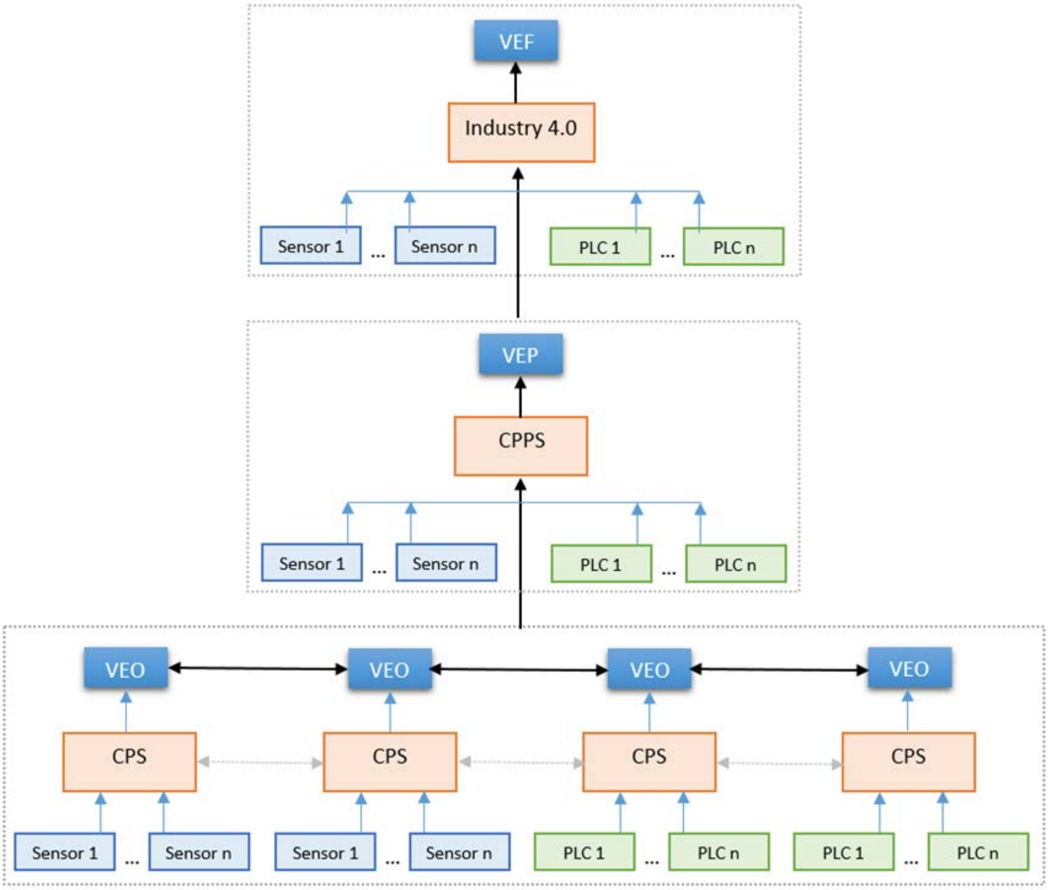

FIGURE 3 VEO-VEP-VEF support to Industry 4.0

The bottom level of figure 3 illustrates that VEO provides a knowledge structure for parts involved in the manufacturing process to possess information on themselves and suitable means of communication and therefore themselves form Cyber-physical systems. The VEO-VEP is to be embedded in the process as a whole and in extreme cases can control not only their own logistical path through production, but rather the entire production workflow that concerns them (see VEP in figure 3). VEO-VEP-VEF supplies compressed information suitably derived from the complex interrelationships and communicates in a personalized manner as the basis for their intervention in the process. In this way, a new form of cooperation between processes, machines and parts of machines arises. This will support both short term flexibility and medium-term transformability and thus improve the resilience of production to CPS based Industry 4.0.

Benefits of VEO-VEP-VEF enabled Industry 4.0 are manifold, some important features at different manufacturing levels are listed in table 1. One of the most significant attribute of VEO-VEP-VEF is the self-awareness capability it provides at each component, process and system level. The consequence of self-awareness is that it results in better monitoring, prediction and efficient productivity.

TABLE 1 Salient features and benefits of VEO-VEP-VEF

	VEO-VEP-VEF	
	Attributes	*Benefits*
Object	Self-aware Self-predict Precision Fault detection	Degradation monitoring & remaining useful life prediction
Process	Self-aware Self-predict Self-compare Condition-based monitoring & diagnostics	Up time with predictive health monitoring Productivity & performance
Factory	Self-configure Self-maintain Self-organize Productivity & OEE	Worry-free productivity Lean operations: work and waste reduction

Case Study: Develop VEO-VEP-VEF and explore its semantic capabilities

The objectives of this study is to capture real-time data, convert it into SOEKS, develop VEO, VEP and VEF then finally to perform semantic analysis. The challenge is to utilize manufacturers own experience for better decision making and provide real-time intelligent monitoring scheme. A manufacturing unit having two machines (Smart Machine 1 and Smart Machine 2) and producing a variety of components is considered for this case-study. Input variables and output functions for VEF, VEP, and VEO in this case study are presented in the Appendix in tables 4, 5, and 6. Figure 4 exhibits that variables (see VEO Input variables in table 6 in the Appendix) of smart machine 1 and smart machine 2 are captured by the sensors, CPS, PLC etc.

then send to Information processing and semantic analysis (IPSA) centre of the manufacturing unit. At IPSA the information is normalized in the SOEKS formats and then converted into VEO for machines.

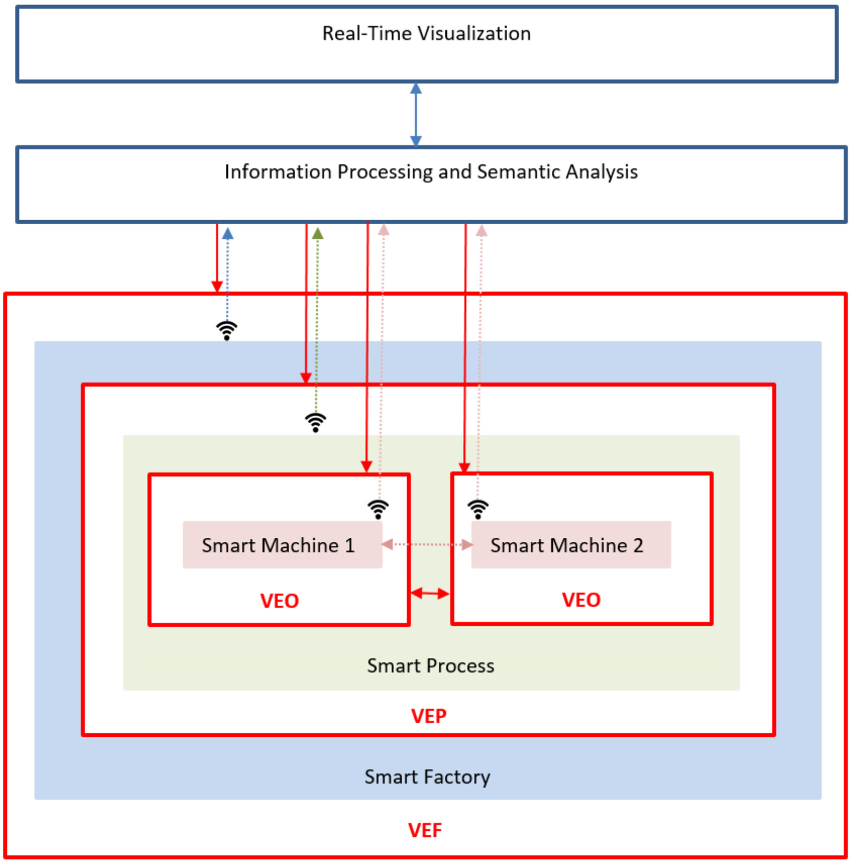

FIGURE 4 Framework for case study

The next level (see Smart Process in figure 4) of this set-up involves the process level information (see VEP Input Variable in table 5 in the Appendix) along with the already developed VEOs at previous level. As shown in figure 4 that a smart process will be capturing process information and transmitting it to IPSA, there it will be transformed into VEP.

The VEF of an intelligent manufacturing unit is the integration of Smart Factory level information (VEF Input Variables in table 4 in the Appendix) along with VEPs and VEOs.

As discussed the captured input variables of VEO, VEP and VEF goes to IPSA where they are converted into SOEKS-variables and also corresponding SOEKS-functions are calculated. For this case-study SOEKS-variables at VEO level are *Depth of Cut, Feed, Speed* etc. and SOEKS-functions is *Tool Life* (see table 6 in the Appendix). Similarly, table 5 and table 6 (in the Appendix) shows SOEKS-variables and SOEKS-functions for VEP and VEO defined and evaluated in IPSA. Thus each row in these tables represents an experience at individual level i.e. VEO_Exp, VEP_Exp and VEF_Exp-.

The other features of the proposed framework are the capabilities to perform semantic analysis like similarity-identification, phenotype calculation etc. and real-time visualization ability at each manufacturing level. In the next subsections semantic capabilities of VEO-VEP VEF are presented.

Similarity Identification calculation

Given a pair of Sets of Experience $vefDNA_i$ (entire VEF repository) and $querySOE_j$ (SOE made up of query) ∈ *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 $k \in vefDNA_i$ and $querySOE_j$. The Euclidean distance measure has been selected based upon its simplicity and extended use. Besides, a normalization form was included following the notion of range of comparison, that is, the maximum function. The similarity metric takes the following equation:

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

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

Phenotype calculation

The SOEKS structure are several elements connected (variables and functions) among them imitating part of a long strand of DNA, that is, a gene (Sanín 2007). A SOE can be assimilated to a gene, and, in the same way as a gene produces a *phenotype*, a SOE produces a value of a decision in terms of its objective functions. Such a value of a decision is of the kind of multi-objective optimization processes (MOO). This value of decision is what is called the *efficiency* of the SOE. The *efficiency* or *phenotype value* is a combination of the objective functions and the effect values of the variables The SOEKS, in its functions, holds weight values (w) for each of them. Efficiency estimation is mathematically calculated as:

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

w_{Fi} is the weight associated to function *Fij*. Variables and phenotypes of the Sets of Experience can be categorized and organized to mine them, as if variables were features and phenotypes were classes. Consequently, interesting results and relationships from the variables and the phenotypes can be extracted, establishing a process of knowledge discovery.

The proposed framework offers users the capability to query VEO-VEP-VEF repository and can find the most similar experience at every level. A query can be formed through a simple graphical user interface (GUI) as shown in figure 5. In the GIU, first the user selects the product to be manufactured (*Product-A*) then clicks

‘ADD Product’ button, then the factory level parameters required for manufacturing *Product-A* populates in the ‘Select Variable’ list-box. Then the user selects a variable and enters the value of that variable in the text-box. Multiple variables can be selected. Then all the selections are combined to build a query by clicking ‘add Query’ button. The query showed in build query text box of figure 5 is:

querySOE = (Product =A, Operating Time = 400, Total Pieces = 15,000, Good Pieces = 1450)

Finally, user clicks ‘run Query’ button and the best SOE which matches the query is returned to the user as shown in solution text-box of figure 5. In the ‘VEF Experience Code’ text-box, the code of the most similar VEF-SOE along with its similarity with the query-SOE is displayed. In the ‘VEP Experience Code’ text-box, the VEP code for the above displayed VEF-SOE is shown and in ‘VEO Experience Code’ text-box code for all the associated VEOs to the above displayed VEP-VEF are shown.

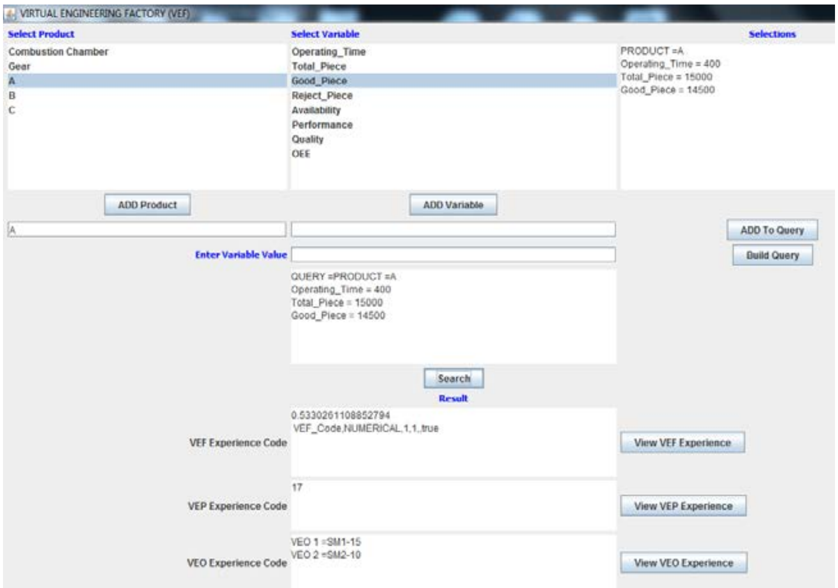

FIGURE 5 GUI for building query and viewing results

Results

In the VEO-VEP-VEF framework linkage of the different levels is from top to bottom i.e. VEF will have linkages of VEP and VEO (see figure 1 and figure 2). Similarly, VEP will have linkage of VEOs whereas VEOs will not have any connections with VEP and VEF. There are two methods of calculating the similarity-identification. First is the actual combined experience that occurred at each level in that manufacturing unit. And the second method is to find most suitable experience individually at each level and then by combining the similarity-identification through Phenotyping create a new virtual experience for the entire factory.

For this case-study the possible query structures, the levels through which it can be executed as well as the structure of solutions are shown in table 2.

Please insert Table 2 here.

Although *Query-1* has variables only of VEF but since VEF is linked with VEP and VEO thus *Result-1* show experience at factory level i.e. VEF_Exp and linked process experience i.e. VEP_Exp and object experience i.e. VEO_Exp. Similarly, structure of *Query-2* and *Query-3* and corresponding structure of *Result-2* and *Result-3* are shown in table 2.

Table 3 illustrates the mechanism to achieve a result with respect to a query.

Please insert Table 3 here.

For the sample test query shown in table 2 there can have three possible cases:

- If VEF is having highest priority, then VEF variables will be queried through *Query-1*. Although only VEF variables are queried result will be VEF_Exp along with corresponding VEP_Exp and VEO_Exp as they are linked from top to bottom. Similarity calculation between *Query-1* and VEF shown in figure 6 suggests that most similar factory experience is VEF_Exp =1 and the linked process experience is VEP_Exp = 17 and object experience is VEO_Exp = 15 (see table 3). In this case there is no phenotyping as there is only one experience at each level thus the final result as shown in table 3 is VEF_Exp = 1, VEP_Exp = 17 and VEO_15.

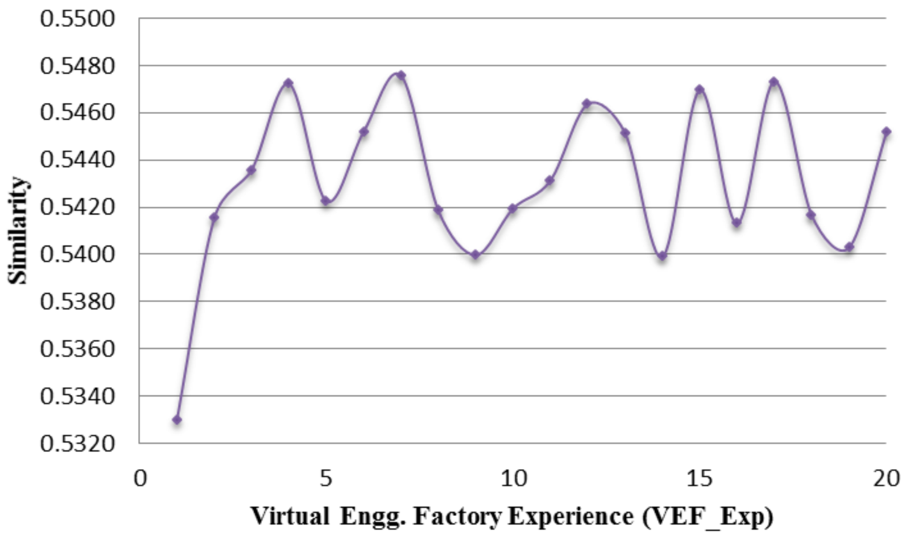

FIGURE 6 Similarity Calculation for Query-1

- If VEP is having highest priority in that case VEF_Exp will be obtained by executing *Query-1*. As mentioned in previous case *Query-1* will not only give VEF_Exp but also corresponding linked VEP_Exp and VEO_Exp (i.e. VEF_Exp =1, VEP_Exp =17, VEO_Exp =15). Since the priority is for VEP, VEP level can also be queried by *Query-2*. Similarity calculation between *Query-2* and VEP shown in figure 7 indicates the most similar process experience is VEP_Exp'=11 and the linked object experience is VEO_Exp' = 8. So the possible solutions can be the combination of the results of *Query-1* and *Query-2* (see table 3). Here the Phenotyping feature of Decisional DNA is utilized to achieve the best SOE at each level among the different results obtained from *Query-1* and *Query-2*. So, phenotype calculation can be obtained between VEP_Exp=17, VEP_Exp' =11 for VEP and VEO_Exp =15, VEO_Exp' = 8 for VEO. Thus the final result in this case is VEF_Exp = 1, VEP_Exp = 11 and VEO_Exp = 8.

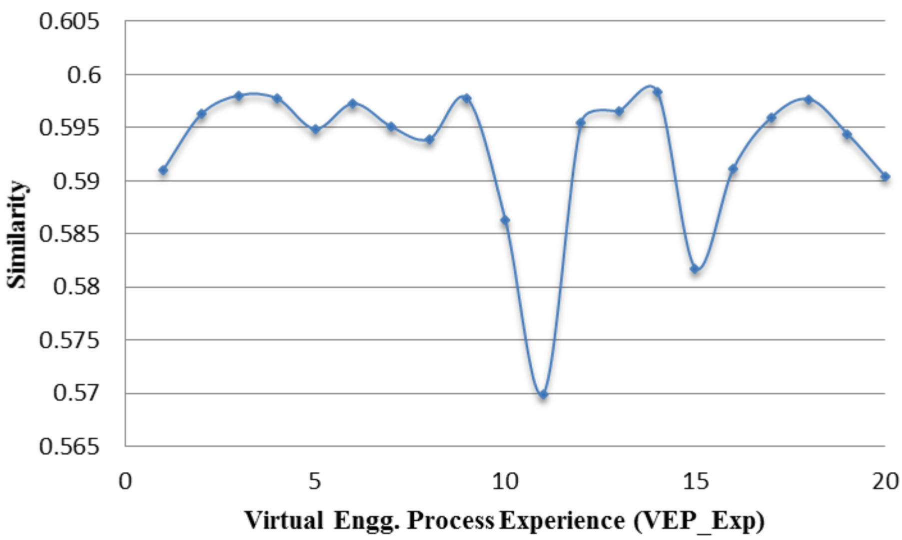

FIGURE 7 Similarity Calculation for Query-2

- If the VEO is having the priority in that case VEF_Exp and VEP_Exp can be achieved as discussed in above. For VEO there can three different SOEs, first two (VEO_Exp and VEO_Exp') can be obtained by executing *Query-1* and *Query-2*. The third SOE (VEO_Exp'') is obtained by executing *Query-3*, in this case phenotyping will be among VEO_Exp =15, VEO_Exp'= 8 and VEO_Exp'' = 3. In this case the VEO has the highest priority thus the final result after phenotype calculation as shown in table 3 is VEF_Exp = 1, VEP_Exp = 17, VEO = 3.

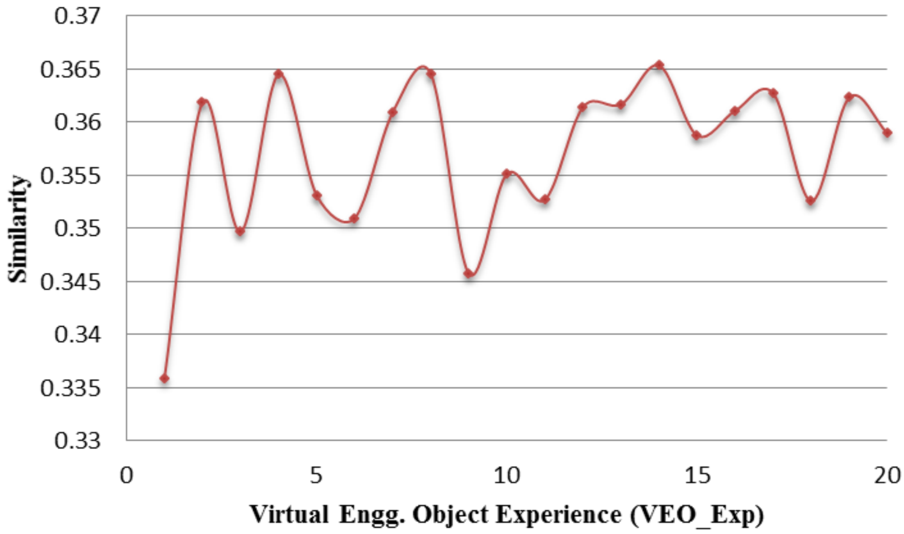

FIGURE 8 Similarity Calculation for Query-3

The benefit of using this approach is that two type of results can be attained. First, the most similar combined experience that occurred at each level of VEF, VEP and VEO can be identified. Secondly, each level of the framework can be treated as independent phase and according to requirement best experience be selected. These independent SOEs are combined together to create a new virtual experience. Thus, providing more options to the practitioners for effective decision making.

Conclusions

This paper throws lights upon basic principle and the role of VEO-VEP-VEF in designing and developing Industry 4.0. It also focuses how the similarity-identification and phenotyping features of DDNA associated with VEO-VEP-VEF can be exploited for creating new virtual experience from its own experience. These semantic analysis features along with visualization capabilities of VEO-VEP-VEF helps in attaining the inherent Industry 4.0 features like self-awareness, real-time monitoring and effective decision making.

TABLE 2 Query and result structure

Sample Query Structure	Query level	Result Structure	Sample Test Query
Query-1 = (Operating Time, Total Pieces, Good Pieces)	VEO-VEP-VEF	Result-1 = VEF_Exp, VEP_Exp, VEO_Exp	[(Operating Time = 400, Total Pieces = 15,000, Good Pieces = 1450), (Machining Time = 30, Idle Time = 60), (Depth of Cut = 50, Speed = 450, Feed = 1.5)]
Query-2 = (Machining Time, Idle Time)	VEP-VEO	Result-2 = VEP_Exp’, VEO_Exp’	
Query-3 = (Depth of Cut, Speed, Feed)	VEO	Result-3 = VEO_Exp’’	

TABLE 3 Query execution mechanism

Priority	Query Type	Possible Results	Phenotyping (~)	Final Result
VEF	Query-1	VEF_Exp=1, VEP_Exp=17, VEO_Exp=15	No	VEF_Exp =1, VEP_Exp = 17, VEO_Exp = 15
VEP	Query-1 Query-2	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	Query-1 Query-2 Query-3	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, VEO_Exp’’=3 VEF_Exp=1, VEP_Exp=17, VEO_Exp’’=3	(VEP_Exp=17) ~ (VEP_Exp’=11) (VEO_Exp=15) ~(VEO_Exp’=8)~(VEO_Exp’’=3)	VEF_Exp = 1, VEP_Exp = 17, VEO_Exp = 3

Appendix

TABLE 4 VEF input variables and output functions

	VEF Input Variables			Output Variables				
VEF_Exp	Operating Time(min)	Total Pieces	Good Pieces	Reject Pieces	Availability	Performance	Quality	OEE
1	296	14,751	14,492	259	0.7048	0.8306	0.9824	0.5751
2	449	12,785	12,517	268	1.0690	0.4746	0.9790	0.4967
3	352	19,071	18,703	368	0.8381	0.9030	0.9807	0.7422
4	240	10,865	10,389	476	0.5714	0.7545	0.9562	0.4123
5	434	18,555	18,109	446	1.0333	0.7126	0.9760	0.7186
6	467	10,623	10,267	356	1.1119	0.3791	0.9665	0.4074
7	159	19,820	19,624	196	0.3786	2.0776	0.9901	0.7787
8	472	17,186	16,711	475	1.1238	0.6069	0.9724	0.6631
9	418	17,478	17,089	389	0.9952	0.6969	0.9777	0.6781
10	385	19,583	19,457	126	0.9167	0.8477	0.9936	0.7721
11	430	11,149	10,940	209	1.0238	0.4321	0.9813	0.4341
12	256	19,565	19,362	203	0.6095	1.2738	0.9896	0.7683
13	270	12,152	11,698	454	0.6429	0.7501	0.9626	0.4642
14	375	17,013	16,633	380	0.8929	0.7561	0.9777	0.6600
15	226	11,272	10,773	499	0.5381	0.8313	0.9557	0.4275
16	261	16,016	15,767	249	0.6214	1.0227	0.9845	0.6257
17	278	10,135	9,744	391	0.6619	0.6076	0.9614	0.3867
18	482	16,781	16,625	156	1.1476	0.5803	0.9907	0.6597
19	473	16,272	16,055	217	1.1262	0.5734	0.9867	0.6371
20	312	19,421	19,148	273	0.7429	1.0374	0.9859	0.7598

TABLE 5 VEP input variables and output functions

	VEP Input Variables		Output Variables	
VEP_Exp	Machining Time(min)	Idle Time(min)	Setup Time(min)	Surface Finish
1	27	29	83	Smooth
2	16.3333	32.66667	49	Fine
3	12.1666	24.33333	36.5	Smooth
4	13	26	39	Rough
5	18.6666	37.33333	56	Fine
6	14.1666	28.33333	42.5	Smooth
7	18.3333	36.66667	55	Rough
8	20	40	60	Fine
9	13	26	39	Smooth
10	26.3333	52.66667	79	Rough
11	30.1666	60.33333	90.5	Fine
12	17.6666	35.33333	53	Smooth

13	15.6666	31.33333	47	Rough
14	11.1666	22.33333	33.5	Fine
15	32	64	96	Smooth
16	23	46	69	Rough
17	16.8333	33.66667	50.5	Fine
18	13.1666	26.33333	39.5	Smooth
19	19.3333	38.66667	58	Rough
20	23.66667	47.33333	71	Fine

TABLE 6 VEO input variables and output functions

		VEO Input Variables			Output Variables
VEO_Exp	**Machine**	**Depth of Cut(mm)**	**Speed(rpm)**	**Feed(mm)**	**Tool Life(min)**
1	M1	47	459	1.5	6739.695
2	M2	48	190	0.7	7354.066
3	M1	51	478	1.8	7612.62
4	M2	38	121	1.2	3522.131
5	M1	46	471	1.9	5551.029
6	M2	52	484	1.3	9031.615
7	M1	55	262	1.1	9657.697
8	M2	35	134	1.8	1629.253
9	M1	52	442	1.4	8694.768
10	M2	53	475	0.8	10102.63
11	M1	54	413	1.7	8751.62
12	M2	55	304	0.9	10099.86
13	M1	37	335	1.2	3835.568
14	M2	37	313	0.7	4436.902
15	M1	41	265	1.4	4404.831
16	M2	47	307	0.7	7420.59
17	M1	42	103	1.8	3370.716
18	M2	53	373	1.4	8816.126
19	M1	38	392	0.7	4919.562
20	M2	43	478	0.5	6842.263

References

Böhler, T. M. *Industrie 4.0-Smarte Produkte und Fabriken revolutionieren die Industrie* 2012 [cited 01/04/2015. Available from http://www.produktion.de/automatisierung/industrie-4-0-smarte-produkte-und-fabriken-revolutionieren-die-industrie/.

Evans, Peter C., and Marco Annunziata. *Industrial Internet: Pushing the Boundaries of Minds and Machines* 2012 [cited 06/04/2015. Available from http://www.ge.com/docs/chapters/Industrial_Internet.pdf.

Henning Kagermann, Wolfgang Wahlster, Johannes Helbig. *Recommendations for implementing the strategic initiative INDUSTRIE 4.0* 2013 [cited 01/04/2015. Available from http://www.acatech.de/fileadmin/user_upload/Baumstruktur_nach_Website/Acatech/root/de/Material_fuer_Sonderseiten/Industrie_4.0/Final_report__Industrie_4.0_accessible.pdf.

Hermann, Mario, Tobias Pentek, and Boris Otto. 2015. Design Principles for Industrie 4.0 Scenarios: A Literature Review http://www.snom.mb.tu-dortmund.de/cms/de/forschung/Arbeitsberichte/Design-Principles-for-Industrie-4_0-Scenarios.pdf.

Kyoung-Dae, Kim, and P. R. Kumar. 2012. "Cyber-Physical Systems: A Perspective at the Centennial." *Proceedings of the IEEE* no. 100 (Special Centennial Issue):1287-1308. doi: 10.1109/JPROC.2012.2189792.

Lee, E. A. 2008. Cyber Physical Systems: Design Challenges. Paper read at 11th IEEE International Symposium on Object Oriented Real-Time Distributed Computing (ISORC), 5-7 May 2008.

Lee, Edward A., and Sanjit A. Seshia. 2014. *Introduction to Embedded Systems, A Cyber-Physical Systems Approach*. 1.5 ed.

Lui Sha, Sathish Gopalakrishnam, Xue Liu, Qixin Wang. "Cyber-Physical System: A New Frontier." In *Machine Learning in Cyber Trust*, edited by Philip S. Yu Jeffrey J. P. Tsai, 3-12. Springer.

Masood, Tariq, Rajkumar Roy, Andrew Harrison, Yuchun Xu, Stephen Gregson, and Carl Reeve. 2014. "Integrating through-life engineering service knowledge with product design and manufacture." *International Journal of Computer Integrated Manufacturing* no. 28 (1):59-74. doi: 10.1080/0951192X.2014.900858.

Posada, Jorge, Carlos Toro, Inigo Barandiaran, David Oyarzun, Didier Stricker, Raffaele de Amicis, Eduardo B. Pinto, Peter Eisert, Jurgen Dollner, and Ivan Vallarino. 2015. "Visual Computing as a Key Enabling Technology for Industrie 4.0 and Industrial Internet." *Computer Graphics and Applications, IEEE* no. 35 (2):26-40. doi: 10.1109/MCG.2015.45.

Sanín, C. 2007. "Smart Knowledge Management System." *Thesis of Doctor of Philosophy Degree From The University Of Newcastle, Department Of Mechanical Engineering, Newcastle, Australia*.

Sanín, Cesar, Leonardo Mancilla-Amaya, Zhang Haoxi, and Edward Szczerbicki. 2012. "Decisional DNA: The concept and its implementation platforms." *Cybernetics and Systems* no. 43 (2):67-80. doi: 10.1080/01969722.2012.654069.

Sanín, Cesar, Leonardo Mancilla-Amaya, Edward Szczerbicki, and Paul CayfordHowell. 2009. "Application of a Multi-domain Knowledge Structure: The Decisional DNA." In *Intelligent Systems for Knowledge Management*, edited by NgocThanh Nguyen and Edward Szczerbicki, 65-86. Springer Berlin Heidelberg.

Sanin, Cesar, Carlos Toro, Zhang Haoxi, Eider Sanchez, Edward Szczerbicki, Eduardo Carrasco, Wang Peng, and Leonardo Mancilla-Amaya. 2012. "Decisional DNA: A multi-technology shareable knowledge structure for decisional experience." *Neurocomputing* no. 88 (0):42-53. doi: http://dx.doi.org/10.1016/j.neucom.2011.08.029.

Shafiq, Syed Imran, Cesar Sanin, and Edward Szczerbicki. 2014. "Set of Experience Knowledge Structure (SOEKS) and Decisional DNA (DDNA): Past, Present and Future." *Cybernetics and Systems* no. 45 (02):200-215. doi: 10.1080/01969722.2014.874830.

Shafiq, Syed Imran, Cesar Sanin, Edward Szczerbicki, and Carlos Toro. 2013. Using Decisional DNA To Enhance Industrial And Manufacturing Design: Conceptual Approach. Paper read at Information Systems Architecture and Technology, 22 – 24 September 2013, at Szklarska Poreba, Poland.

Shafiq, Syed Imran, Cesar Sanin, Edward Szczerbicki, and Carlos Toro. 2014a. "Decisional DNA Based Framework for Representing Virtual Engineering Objects." In *Intelligent Information and Database Systems*, edited by

NgocThanh Nguyen, Boonwat Attachoo, Bogdan Trawiński and Kulwadee Somboonviwat, 422-431. Springer International Publishing.

Shafiq, Syed Imran, Cesar Sanin, Edward Szczerbicki, and Carlos Toro. 2014b. "Implementing Virtual Engineering Objects (VEO) with the Set of Experience Knowledge Structure (SOEKS)." *Procedia Computer Science* no. 35 (0):644-652. doi: http://dx.doi.org/10.1016/j.procs.2014.08.146.

Shafiq, Syed Imran, Cesar Sanin, Edward Szczerbicki, and Carlos Toro. 2014c. "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, Z. Wilimowska, 183-192 Wroclaw: Wroclaw University of Technology Press.

Shafiq, Syed Imran, Cesar Sanin, Edward Szczerbicki, and Carlos Toro. 2015a. "Virtual Engineering Object / Virtual Engineering Process: A specialized form of Cyber Physical System for Industrie 4.0." *Procedia Computer Science* no. 60:1146-1155. doi: http://dx.doi.org/10.1016/j.procs.2015.08.166.

Shafiq, Syed Imran, Cesar Sanin, Edward Szczerbicki, and Carlos Toro. 2015b. "Virtual Engineering Objects: Effective Way of Knowledge Representation and Decision Making." In *New Trends in Intelligent Information and Database Systems*, edited by Dariusz Barbucha, Ngoc Thanh Nguyen and John Batubara, 261-270. Springer International Publishing.

Shafiq, Syed Imran, Cesar Sanin, Edward Szczerbicki, and Carlos Toro. (in press). Decisional DNA based Conceptual Framework for Smart Manufacturing. In *36th International Conference Information Systems Architecture and Technology*. KARPACZ, POLAND.

Shafiq, Syed Imran, Cesar Sanin, Carlos Toro, and Edward Szczerbicki. 2015. "Virtual Engineering Object (VEO): Toward Experience-Based Design and Manufacturing for Industry 4.0." *Cybernetics and Systems* no. 46 (1-2):35-50. doi: 10.1080/01969722.2015.1007734.

Szczerbicki, Edward, Cesar Sanin, and Syed Imran Shafiq. 2015. Set of Experience and Decisional DNA: Towards brains of cyber-physical systems and industry of the future. Paper read at IEEE 2nd International Conference on Cybernetics (CYBCONF), at Gydnia, Poland. IEEE Catalog Number: CFP1530U-USB.