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Towards an experience based collective computational intelligence for manufacturing

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Abstract

Knowledge based support can play a vital role not only in the new fast emerging information and communication technology based industry, but also in traditional manufacturing. In this regard, several domain specific research endeavors have taken place in the past with limited success. Thus, there is a need to develop a flexible domain independent mechanism to capture, store, reuse, and share manufacturing knowledge. Consequently, innovative research to develop knowledge representation models of an engineering object and engineering process called Virtual engineering object (VEO) and Virtual engineering process (VEP) has been carried out and extensively reported. This paper proposes Virtual engineering factory (VEF), the final phase to create complete virtual manufacturing environment which would make use of the experience and knowledge involved in the factory at all levels. VEF is an experience based knowledge representation for a factory encompassing VEP and VEO within it. The novelty of this approach is that it uses manufacturer's own previous experience and formal decisions to collect and expand intelligence for future production. The experience based collective computational techniques of Set of Experience Knowledge Structure (SOEKS) and Decisional DNA (DDNA) are used to develop aforesaid models. In this article the concept and architecture of VEF is explained as well as the integration of all three levels of virtual manufacturing i.e. VEO, VEP and VEF is presented. Furthermore, a case-study is presented to validate the practical implementation of the proposed concept. The benefits of this approach are manifold as it creates the environment for collective intelligence of a factory and enhances effective decision making. The models and research presented here embody the important first step into developing the future computational setting as required by the emerging next generation of cyber-physical systems.

Keywords: Set of Experience Knowledge Structure, Decisional DNA, Virtual engineering object (VEO), Virtual engineering process (VEP), Virtual engineering factory (VEF)

1 Introduction

Industrial manufacturing is a complex process involving an environment characterised by a continuous exchange of myriads of data and information. Successful production requires the capability to design and manufacture a large number of product variants rapidly and collaboratively, based on design principles [1]. Efficient decision-making processes appear to be the best strategy to cope successfully with the variable nature of industrial manufacturing. Thus, practitioners must generate elements that support effective decision making for manufacturers. One such element is knowledge-based manufacturing. This practice involves the organisation's most valuable asset: knowledge. If knowledge is managed in the right form and the right technology is used, manufacturers will be able to apply it as a powerful computational intelligence tool in the quest for efficiency, effectiveness and competitiveness [2, 3].

Manufacturing organisations are seeking knowledge-based support, not only to meet current market demands, but also to prepare for future industrial trends [4]. Many knowledge-based techniques used in the past aimed to organize past, present and future information [5, 6]. Some important objectives of these techniques include sharing information, forecasting and generating new knowledge [7-10]. Knowledge-based techniques used in the past had limited success due to several shortcomings (e.g., they were time-consuming, and not very intelligent). Moreover, most of these knowledge systems were designed for a specific domain, which significantly reduces their applicability to any other area and makes them less flexible and versatile [11-14]. They also lack a standard knowledge representation (KR), as well as the ability to share and exchange information. Further, they fail to consider formal experience. Therefore, a comprehensive system that uses domain-independent KR and is able to extract, compute, and refine existing knowledge is yet to be fully explored and remains the focus of current research [15-17].

Furthermore, efforts are being made around the world to improve the productivity and efficiency in industrial manufacturing which can be achieved by integrating it with Information and Communication Technology (ICT). The main objective behind this integration is to reap the benefits created by the unprecedented advancement and new opportunities shaped in the field of ICT [18-20].

Our contribution to the above discussed scenario is based on the hypothesis that collecting, structuring, storing, and reusing past manufacturing experience and knowledge can significantly help in developing an intelligent system capable of optimal resource management and minimization of waste. Accordingly, Virtual engineering object (VEO) and Virtual engineering process (VEP) which are experienced based knowledge representation of engineering object and process have been already successfully developed and implemented [21-27]. In this paper, the concept of intelligent virtual manufacturing system having three broad levels of VEO, VEP and Virtual engineering factory (VEF) is proposed.

The structure of this paper is as follows: section 2 gives the overview and the central idea of the proposed approach. Also, it deals with the basic concept, architecture and objectives of VEO, VEP and VEF. In section 3, a case-study is presented to demonstrate the implementation of the planned concept and the methodology to extract experience and to reuse it for decision making. Finally, section 4 outlines the potential benefits of this work, conclusions and future work.

2 Methodology to collect experience for intelligent manufacturing

The central aim of this work is to replicate the knowledge and experience of the manufacturing factory and represent it virtually. Figure 1 illustrates this objective. As shown in the figure, the physical manufacturing scenario can be divided into three levels: resources, processes, and factory. In the manufacturing domain, a factory performs various manufacturing processes, and a process in turn uses different resources. For the complete KR of a manufacturing system we divided it into three levels; the first is the resource/object level (VEO), the second is the process level (VEP) and the third is the factory/system level (VEF). Thus, a mechanism to store and reuse experience related to objects, processes and factory working has been developed. KR models of these levels have been developed both separately and in conjunction with each other. As outlined in Section 1, the main aim of this work is to develop a smart knowledge base platform to enhance industrial manufacturing. KR of engineering objects, processes, and system will help optimize assets, machines and whole system, respectively. Critical, effective and creative decisions can be made based on these intelligent virtual manufacturing levels.

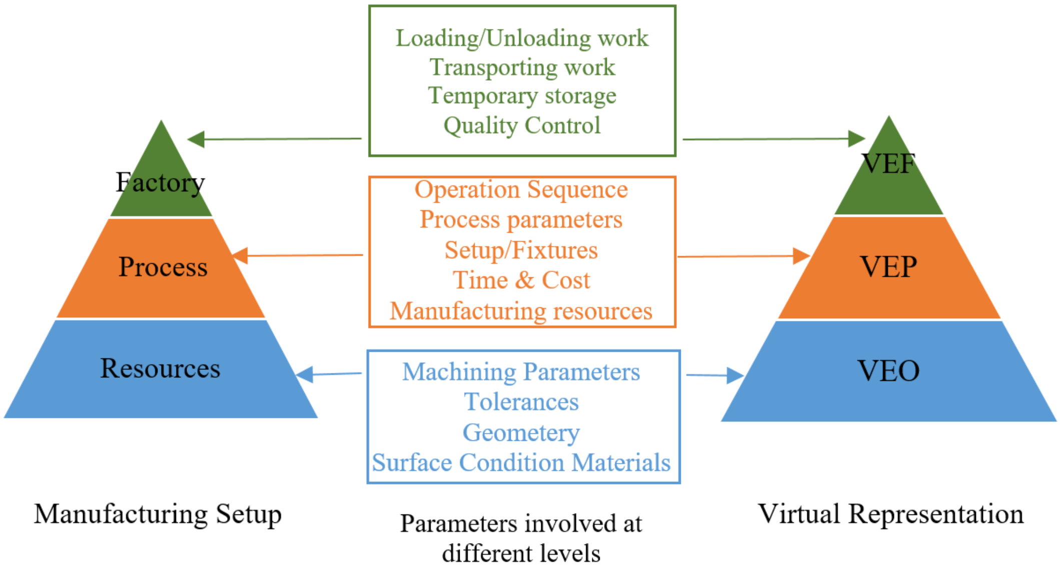

Figure 1 Correlation of physical and the virtual manufacturing world

As depicted in Figure1, a VEO is a representation at the individual object/resource/artefact level, and represents complete information at the machine level such as machining parameters, tolerances, and surface conditions. The VEP deals with information at the process or shop-floor level, such as operation sequences, process parameters, time, and cost. The VEF stores the experience and formal decisions related to various aspects at the system level, such as material handling, storage, quality control, and transportation. Besides representing knowledge at the factory level, the VEF also contains VEOs and VEPs. The combination of VEOs, VEPs and the VEF constitutes the virtual industrial manufacturing platform.

However, industrial manufacturing is a highly complex, creative, and knowledge intensive process involving collaborative information exchange from various sources which changes with changing production conditions. Therefore, for representing such dynamic environment a flexible knowledge structure capable of handling varying nature of parameters at each level is required. The powerful knowledge representation structure facilitating experience based intelligence of Set of experience knowledge structure (SOEKS) and Decisional DNA (DDNA) is used as the technological base for this work. SOEKS-DDNA [28-32] is a unique and single structure for collecting, storing, improving, and reusing experience of intelligent decision-making. SOEKS is composed of variables, functions, constraints and rules associated in a DNA shape permitting the development of the Decisional DNA of an organization which embodies its collective intelligence. Variables normally implicate representing knowledge using an attribute-value language (i.e. by a vector of variables and values), and they are the centre root of the structure and the starting point for the SOEKS. Functions represent relationships between a set of input variables and a dependent variable; moreover, functions can be applied for reasoning about optimal states. Constraints are another way of associations among the variables. They are restrictions of the feasible solutions, limitations of possibilities in a decision event, and factors that restrict the performance of a system. Finally, rules are relationships between a consequence and a condition linked by the logical statements IF-THEN-ELSE. They are conditional relationships that control the universe of variables.

Decisional DNA (DDNA) is a metaphor related to natural DNA and the way it transmits genetic information and knowledge 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. The dynamic structure of SOEKS provides flexibility to the structure of VEO, VEP and VEF. Thus, the broad aim of this research is to develop manufacturing fingerprint or Manufacturing DNA of a company.

As mentioned in section 1, Virtual Engineering Object and Virtual Engineering Process concepts are already developed, implemented and tested [23-25]. For the sake of completeness in the next section, a brief description of VEO and VEP is presented first and then the final phase of virtual manufacturing i.e. Virtual Engineering Factory is discussed along with the integration of all the three phases.

2.1 Virtual engineering object

A Virtual Engineering Object is knowledge representation of an engineering artefact and it has three main features: (i) the embedding of the decisional model expressed by the SOE (ii) a geometric representation, and (iii) the necessary means to relate this virtualization to the physical object being represented [21, 22, 24, 25].

A Virtual Engineering Object is a living representation of an object capable of capturing, adding, storing, improving, sharing, and reusing knowledge through experience in a way similar to a human expert. 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 (manufacturing chromosomes) of an object, namely VEO-Characteristics, VEO-Functionality, VEO-Requirements, VEO-Connections, VEO-Present State, and VEO-Experience as illustrated as cloud architecture in Figure 2.

Virtual Engineering Object is developed on the cradle-to-grave approach, which means that the contextual information and decision making regarding an engineering object right from its inception until its useful life is stored or linked in it. The changing machining conditions such as spindle thermal deformation, tool failure, chatter and work-piece deformation induced by clamping force, cutting force, material inner stress and so on significantly impact machining quality and efficiency. The VEO will cater to these problems relating to decision making that may emerge during the machining process due to complex conditions at the machining level. The technique of SOEKS-DDNA allows VEO not to adhere to any rigid arrangement of parameters which provides dynamicity and flexibility to the structure; such a feature enables VEO to represent complex and discrete engineering objects.

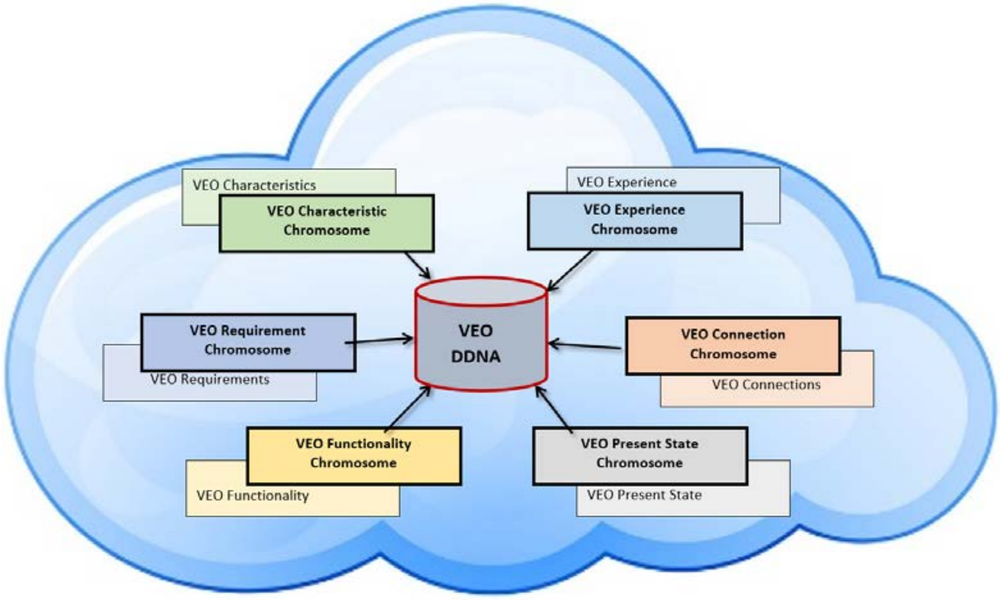

Figure 2 Structure of Virtual Engineering Object (VEO)

2.2 Virtual engineering process

A Virtual Engineering Process is a KR of a manufacturing process/process planning of an artefact that gathers and stores entire shop-floor-level information regarding the operations required, their proper sequence, and the resources (VEOs) needed to manufacture it [23, 24]. The VEP selects the necessary manufacturing operations and determines their sequences, as well as selecting the manufacturing resources needed to transform a design model into a physical component economically and competitively. In addition to this, information of all the VEOs of the resources associated with the process is also linked in VEP. Therefore, to encapsulate knowledge of the above mentioned areas the Virtual Engineering Process is designed having following three main modules (Figure 3):

1. VEP-Operations: All of the information related to the operations that are required to manufacture an engineering component is stored in this VEP module. This includes knowledge in the form of SOEKSs related to operational processes and scheduling. Functional dependencies between operations are also part of VEP-Operations. These are subcategorised and their interaction planning functions are given below:

    - Scheduling route: based on global and local geometry.
    - Processes: process capabilities, process cost.
    - Process parameters: tolerance, surface finish, size, material type, quantity and urgency.

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

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

Moreover, the Virtual Engineering Object information categorised under VEO-Characteristics, VEO-Requirements, VEO-Functionality, VEO-Present State, VEO-Connections and VEO-Experience is also linked in this section.

3. VEP-Experience: Links to SOEKSs of VEOs along with VEPs containing past formal decisions relating to manufacture engineering components are stored in this module. Thus, the information in this module represents links to SOEKSs based on past experience of that particular machine performing a given operation along with operational and routing parameters.

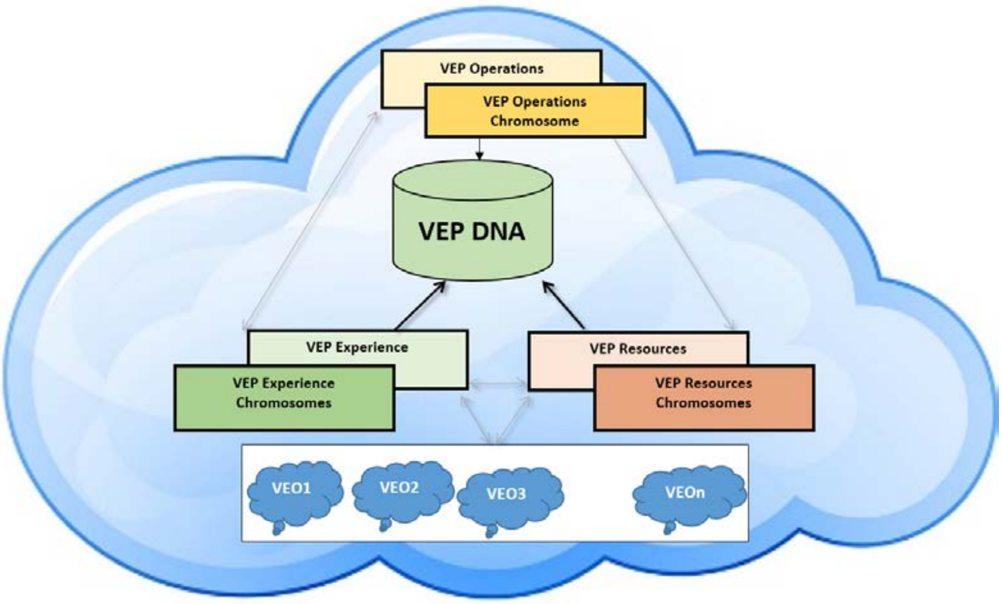

Figure 3 Architecture of Virtual Engineering Process (VEP)

2.3 Virtual Engineering Factory

In this section, the extension of the VEO-VEP concept to the factory level (i.e., Virtual Engineering Factory) is discussed, and a unified architecture covering all three aspects of a manufacturing unit is proposed. A manufacturing factory is a collection of integrated equipment and human resources whose function is to perform one or more processing and/or assembly operations starting with a raw material, part, or set of parts [26, 27]. The main components of a manufacturing system as identified in the literature can be broadly classified as:

- production machines and tools,
- material handling and work-positioning devices,

- computer systems and
- human resources required either full-time or periodically to keep the system running.

Based on the components and their functionality at the factory level, the architecture of Virtual Engineering Factory is conceived. A VEF comprises six elements, each linked to the associated VEPs and VEOs representing complete knowledge and experience related to a manufacturing factory. The arrangement of these six VEF elements, along with their VEOs and VEPs, is shown in Figure 4. The Virtual Engineering Factory elements are as follows:

- VEF-Loading/Unloading: Information related to loading and unloading work units at each station along with the positioning of work units at each station is stored in this module.
- VEF-Transportation: This module deals with information about transporting work units between stations in a multi-station system. Work units either flow through the same sequence of workstations or are moved through a variety of different station sequences. This knowledge is stored in this module.
- VEF-Storage: This module stores all knowledge related to the permanent and temporary storage of tools, objects, raw materials, and work during the manufacturing process.
- VEF-Quality Control: This module contains the quality control strategy adopted, its implementation method, and outcome.
- VEF-Experience: In this module, the entire history of formal decisions made at the factory level, along with links to the VEPs and VEOs related to those decisions is stored. In other words, all past experience is captured in this module.

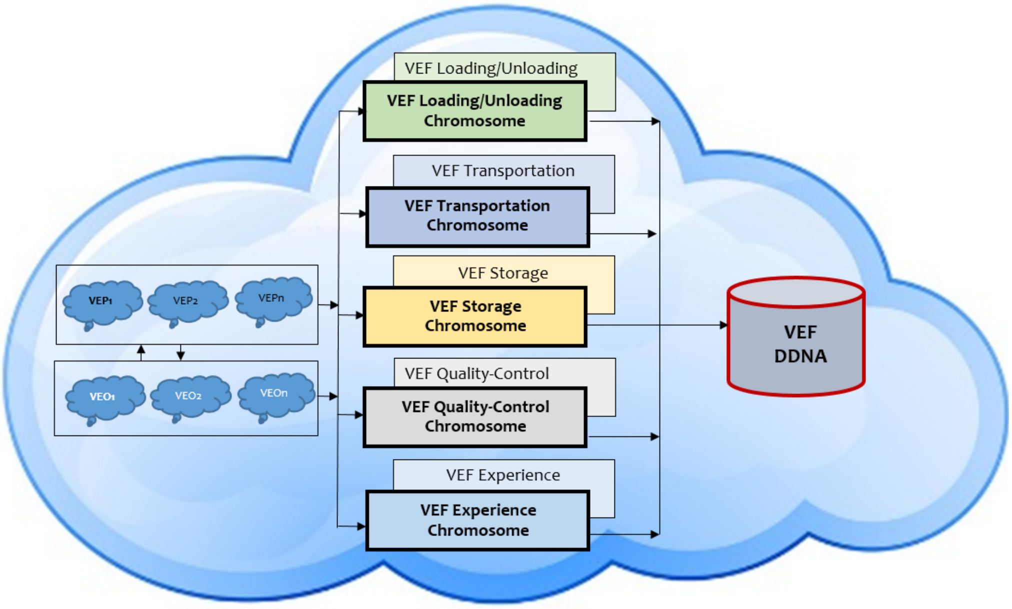

Figure 4 Virtual Engineering Factory architecture linking VEOs and VEPs

Each factory level experience (i.e. VEF-SOEK) is associated with a component (VEP-SOEKS) to be manufactured and that component in turn needs machines/objects (VEO-SEOKS) for its manufacturing. This idea is shown in Figure 4; VEF-DDNA is created by collecting, connecting, and linking VEF-SOEKS, VEP-SOEKS and VEO-SOEKS. Therefore, a Virtual Engineering Factory can be defined as experience-based manufacturing DNA or manufacturing footprints bearing traces of all decisions made at the product, process, and factory levels.

2.4 Salient features of proposed virtual engineering object, process and factory

As mentioned in the previous sections VEO, VEP and VEF are based on the knowledge representation technique of SOEKS and Decisional DNA. This technique is capable of creating Manufacturing DNA (collective computational manufacturing intelligence) as it has manufacturing nucleotides (variables, function, constraints, rules), manufacturing genes (collection of SOEKS), and manufacturing chromosomes (collections of manufacturing genes namely VEO-Characteristics, VEO-Requirement, VEO-Functionality, VEO-Present State, VEO-Connections, VEO-Experience, VEP-Resources, VEP-Operations, VEP-Experience, VEF-Loading/Unloading, VEF-Transportation, VEF-Storage, VEF-Quality Control, VEF-Experience). Experimental case-studies [23, 24] have proven that a DDNA-based VEO-VEP-VEF knowledge system has the following features:

- a versatile and dynamic knowledge structure, which provides the flexibility necessary to change according to the changing situation;
- the ability to store day-to-day explicit experiences in a single structure, which will continuously evolve;
- transportable, adaptable, and shareable knowledge;
- prediction and decision-making abilities based on collected past experience, and
- the ability to achieve decisional trust by having the right quality and quantity of knowledge at the right time.

As shown in Figure 2, 3 and 4, the VEO-VEP-VEF system is also envisaged on a cloud computing platform to facilitate the delivery of information related to multifaceted interrelationships within the modelled state.

3 Case-Study: Creating Manufacturing DNA

The objective of this case-study is to create Manufacturing DNA with retaining, predicting, and decision making capabilities based on the collected past experience.

The Virtual Engineering Factory concept is demonstrated and implemented in a case study of a manufacturing system to produce an engineering component. This case study extends the VEF part of the previous VEP and VEO case studies, which were based on manufacturing a simple combustion chamber in a conventional machining setup [23-25]. The basic operations required to manufacture this combustion chamber are turning, taper turning, and drilling; this information is stored in the Virtual Engineering Process, which is shown as a work-in-process assignment (‘WIPA’) in Figure 5. The manufacturing setup in this case study has two different lathe and drilling machines each. Factory-level information about work-piece loading/unloading, quality control, transportation, storage, and previous experience are stored in the VEF (see Figure 4) and presented as the Set of Experience structure in the Appendix Table 1.

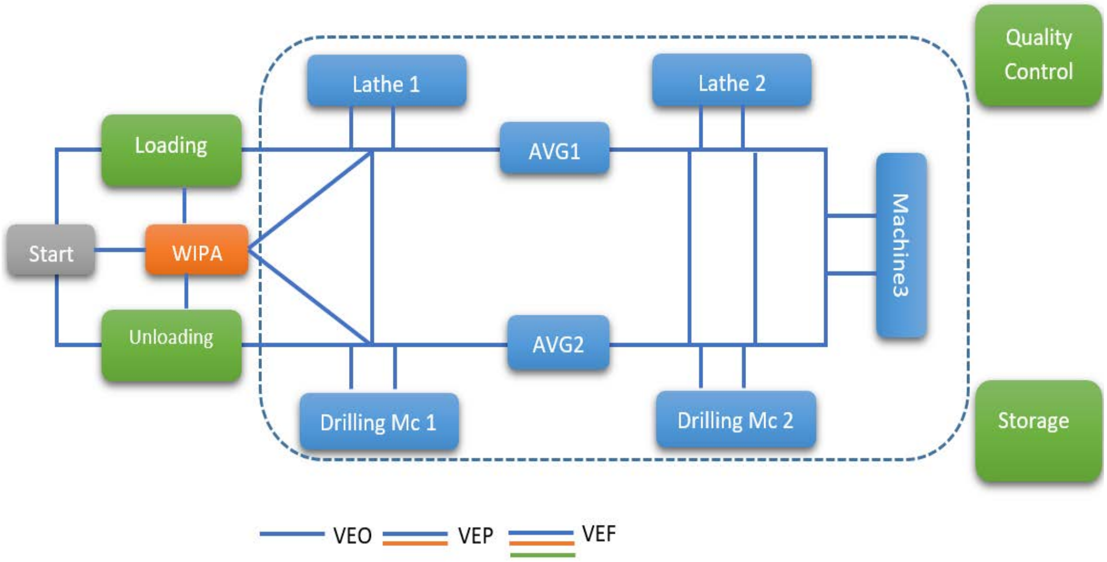

Figure 5 Framework for the case-study involving VEOs, VEPs and VEF

First, VEOs of the machines required to produce the engineering component are developed. Then, the VEPs to produce an engineering component are built based on the case-specific experiences of that manufacturing unit. Finally, the VEF having all of the factory-level knowledge along with links to the VEPs and VEOs is constructed. The VEOs along with experience of the engineering processes (VEPs) form the experience repository of a manufacturing unit. Table 1 (in the Appendix) illustrates the structure of the VEF. Comma separated value (CSV) files storing formal decisions related to VEF-Loading/Unloading, VEF-Transportation, VEF-Storage, VEF-Quality Control, and VEF-Experience were built for the component to be made, that is, a combustion chamber. Although TXT and XML formats can also be used for managing and storing data, but CVS format is selected as data transfer among programs is simpler in it. VEO-DNA and VEP-DNA were already developed in previous case studies [21, 22]. The next objective is to develop VEF-DNA and link it with VEO-DNA and VEP-DNA to create a complete Manufacturing DNA.

Having the CSV files, a parser is written in Java programming language to read information and convert them into SOEKS. The reason for selecting JAVA is because in future this approach can be extended as a web based application. The parser looks for the CSV file, in that file it looks for the word ‘variables’ and starts reading the first row under ‘variables’. After reading all of the variables in the first row, the parser looks for the word ‘functions’ and reads all of the rows under ‘functions’. Next, it looks for the word ‘constraints’ and reads all of the rows under ‘constraints’. All of this information (i.e., the first row under ‘variables’, and all of the rows under ‘functions’ and ‘constraints’) is stored as a single SOE. This cycle is repeated for each row under ‘variables’, along with those under ‘functions’ and ‘constraints’, creating a SOEKS.

The same parsing procedure is repeated for the all other CSV files. Each file representing a category, collection of SOEKS of same category forms a chromosome of either of VEO, VEP or VEF (see Figure 2, Figure 3 and Figure 4). Collection of all chromosomes forms a

Decisional DNA of a VEF, i.e. VEF-DNA. Once the VEF-DNA is constructed, DDNA has a feature that it can be queried [28].

Given a pair of SOE *vefDNAi* (the entire VEO-DNA repository) and *querySOEj* (a SOE made up of the 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 $k \in vefDNAi$ and *querySOEj*. The Euclidean distance measure has been selected on account of its simplicity and extensive use. A normalisation form was also included in keeping with the notion of a range of comparison, that is, the maximum function. The similarity metric takes the following equation:

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

Where $vefDNA_{ik}$ and $querySOE_{jk}$ 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 in $vefDNA_i$.

When a query is generated by a GUI, it is programmatically converted into a query SOE (*querySOE* of Equation 1). Depending whether it is related to the object, process or factory level, the program will continue calculating the similarity of the *querySOE* with each SOEKS stored in the VEF-DNA. Finally, the calculated similarities are sorted and the five most similar SOEKSs are returned.

Figure 6 explains the method used to extract VEF-VEP-VEO knowledge. The experience repository of a variety of components produced in a manufacturing system is first stored in a structured format (see Table 1). When there is a need to produce a new component, the VEF repository is scanned for similar components (a combustion chamber in this case). The VEF reads the experience of that component in its repository and returns information relating to the previous most similar manufacturing experience stored. Next, the query relating to specific factory-level details required for the component is specified. For this query, the VEF returns VEP-SOEKS for process/process planning and VEOs for each operation, along with the SOE that best suits the queried resources details.

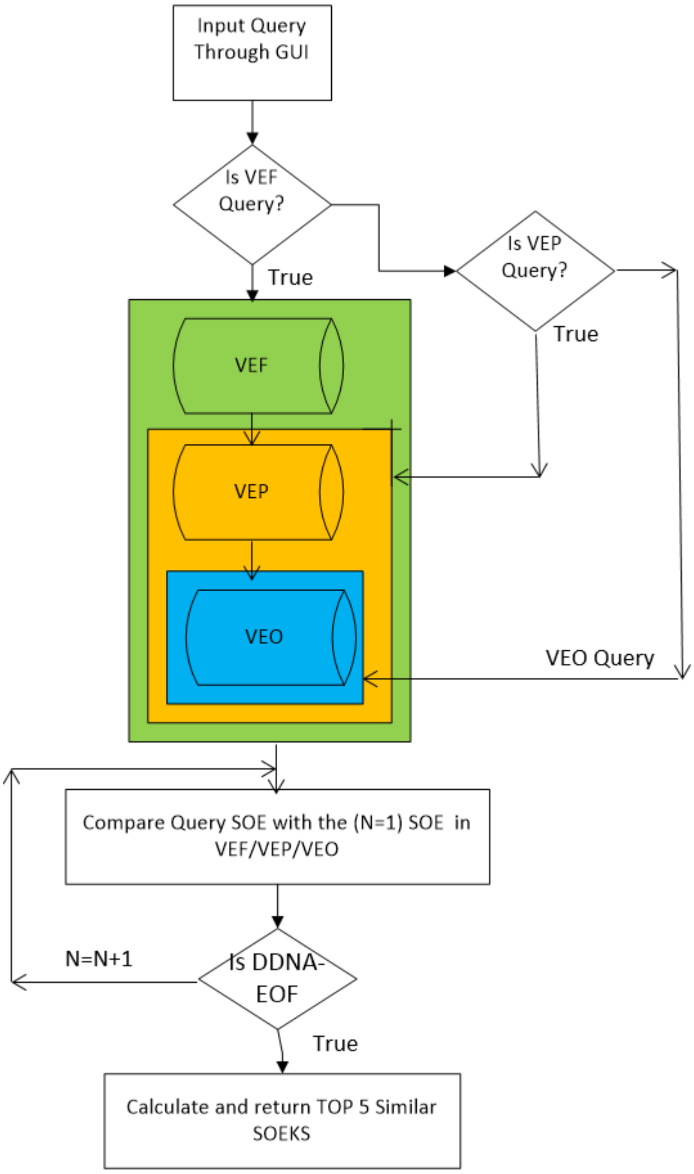

Figure 6 Extracting information from VEF, VEP and VEO

The most similar VEO-SOEKSs are gathered and combined with the most similar VEP-SOEKSs. This information combined with the most similar VEF-SOEKSs forms the solution to the query.

A simple user friendly GUI (see Figure 7) is designed to build queries; user specifies information regarding the product, its variables and variable values. Information is extracted from the VEF-DNA for most similar VEF-SOEKS and further details of VEP-SOEKS and VEO-SOEKS corresponding of that experience can be viewed through GUI.

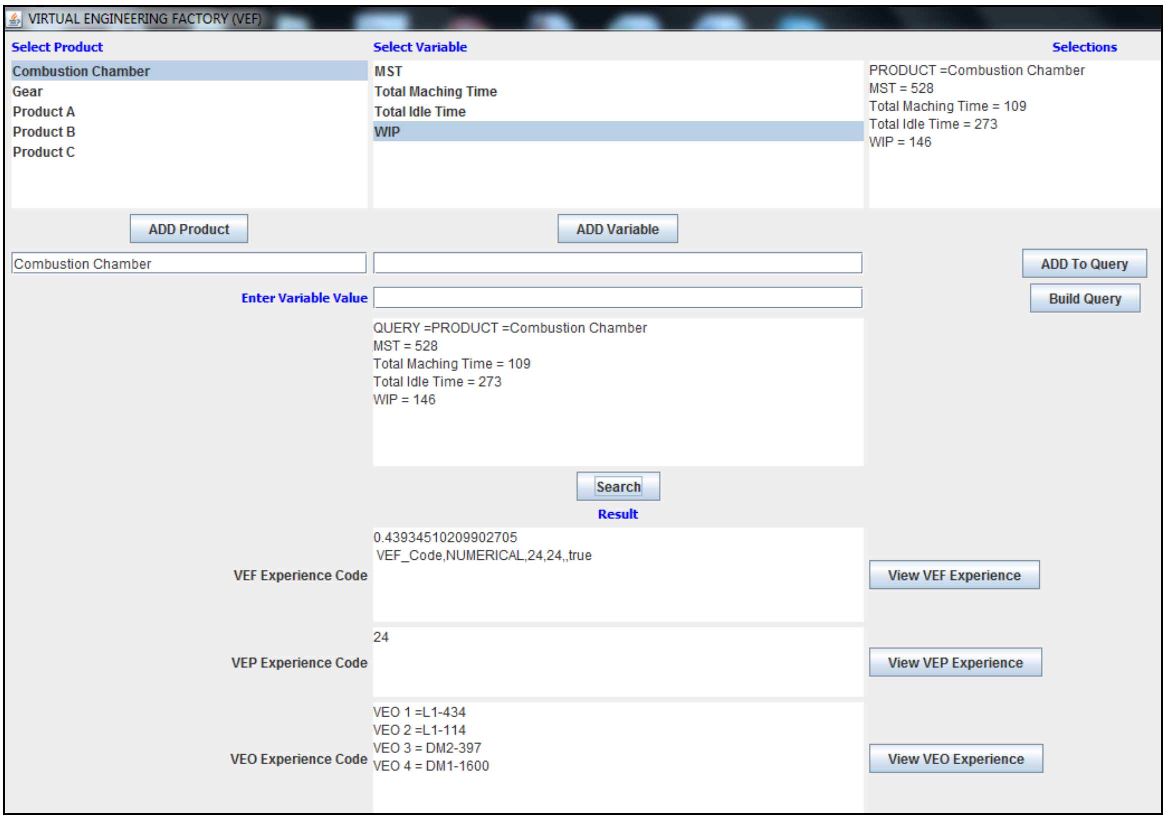

Figure 7 Building a query from GUI

Figure 7 shows execution of a sample query. As depicted in the result section of GUI the user can see the similarity index along with codes of most similar VEF, VEP and VEO SOEKS corresponding to the query. The user can also view the complete VEF-SOE corresponding to the code displayed in the 'VEF Experience Code' text box by clicking on 'View VEF Experience'. Figure 8 shows the following VEF-SOE details: VEF_Code = 24, vepName = COMBUSTIONCHAMBER, vepCode_Exp = 24, Loading_Code = 1, Transportation_Code = 2, Storage_Code = 2, QualityControl_Code = 2, Total Machining Time = 109, Total Idle Time = 273, WIP = 146 and MST = 528.

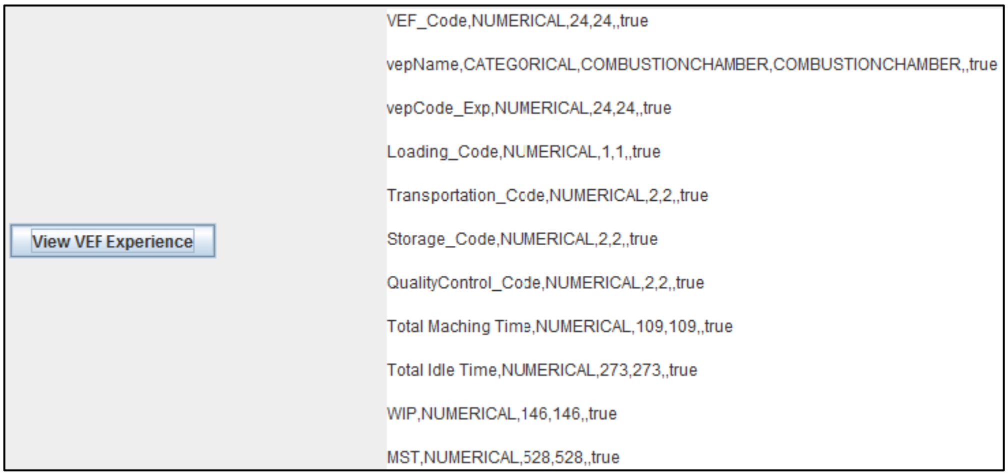

Figure 8 Most similar VEF-SOEKS in the VEF-DNA repository

Likewise, all of the VEP-SOEKSs and VEO-SOEKSs corresponding to ‘VEP Experience Code’ and ‘VEO Experience Code’ can be displayed by clicking the ‘View VEP Experience’ and ‘View VEO Experience’ buttons, respectively.

Princples of this case-study can be followed to effectively scale-up the knowledge represenation of complex industrial set-ups. Thus, flexible and dynamic structures of SOEK-DDNA, VEO, VEP and VEF are capable to representing any manufacturing environment.

3.1 Results and discussion

The implementation of this study was carried on a DELL laptop with the Windows 7 Enterprise operating system, Intel (R) Core (TM) i5-3210M CPU @ 2.50 GHz processor and 8 GB of RAM. The significance of the VEO-VEP-VEF models used in the case study are analysed by doing the following:

- assessing the time taken to create SOEKSs from the VEO, VEP and VEF CSV files
- obtaining the most similar SOE to a query and calculating query execution time
- analysing changes in similarity patterns due to varying query input parameters.

3.1.1 Time taken to create set of experience knowledge structure from the virtual engineering object, process and factory comma-separated values files

The present VEF study comprises SOEKSs from VEF-Loading/Unloading, VEF-Transportation, VEF-Storage, VEF-Quality Control and VEF-Experience having a minimum of 47 variables and 10 constraints (see Appendix Table 1). In addition, VEP-DNA comprises SOEKSs from VEP-Resources, VEP-Operations and VEP-Experience, having a minimum of 20 variables and 12 constraints. Moreover, the VEO-DNA comprises SOEKSs from VEO-Characteristics, VEO-Functionality, VEO-Requirements, VEO-Present State, VEO-Connections and VEO-Experience, having 53 variables, 3 functions and 28 constraints. For testing purposes, we queried VEO-Drilling Machine from a repository of 2256 SOEKSs, VEO-Lathe Machine from 1920 SOEKSs, VEP from 320 SOEKSs and VEF from 26 SOEKSs.

The parsing process of the VEF, VEP and VEO decisional chromosomes were executed, producing a parsing time of 664.0 ms for VEO_Drilling, 504.0 ms for VEO_Lathe, 161.0 ms for the VEP and 10 ms for the VEF (see Figure 9). This is considered an excellent time taking into account the fact that these SOEs are very complex due to the number of variables, functions and constraints involved, adding up to a total of 141 key features per formal decision event.

The model is fairly effective as far as the time taken to parse VEO, VEP and VEF is concerned.

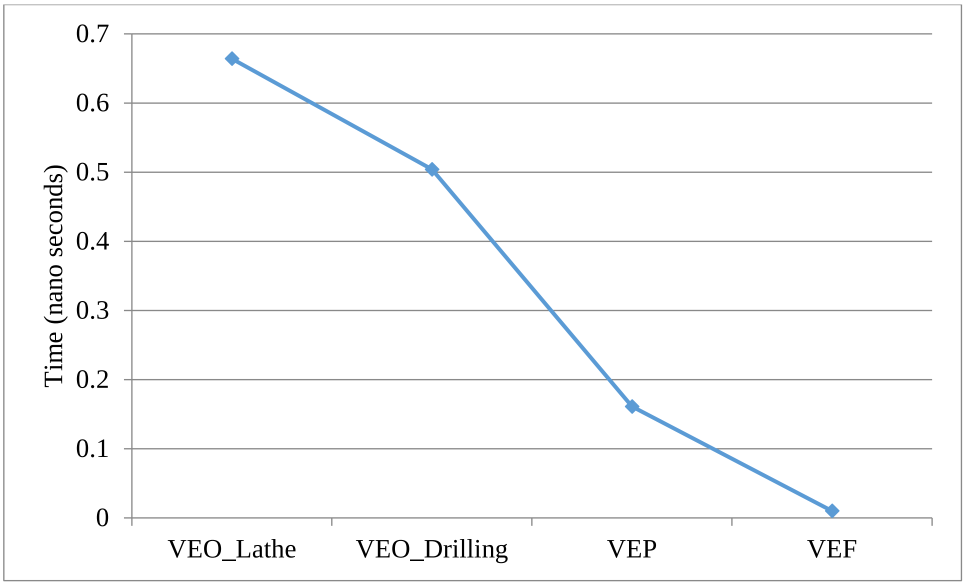

Figure 9 Time taken to parse VEO, VEP and VEF

3.1.2 Obtaining the most similar set of experience to a query and calculating execution time

Table 2 in Appendix provides a list of sample queries that were executed to find the most similar SOEs. For example, in Query 1, VEF similarity is calculated for 'Combustion Chamber' where MST = 528 min, WIP = 146 mins, Machining Time = 109 mins and Idle Time = 273.

Figure 10 illustrates the execution of this query. VEF-DNA returns the five most similar SOEKSs, which in this particular case are VEF_Code no 24, 23, 22, 21 and 20 having similarities 0.43934, 0.45154, 0.45384, 0.45537 and 0.45654, respectively. The time taken to execute this query is 6.766 ns which is fairly short.

To determine the performance and robustness of our model, a set of queries having a decreasing number of variables and all other parameters the same were executed. As illustrated in Figure 10, as the number of query variables decreases the similarity value increases, which validates the efficiency of the model.

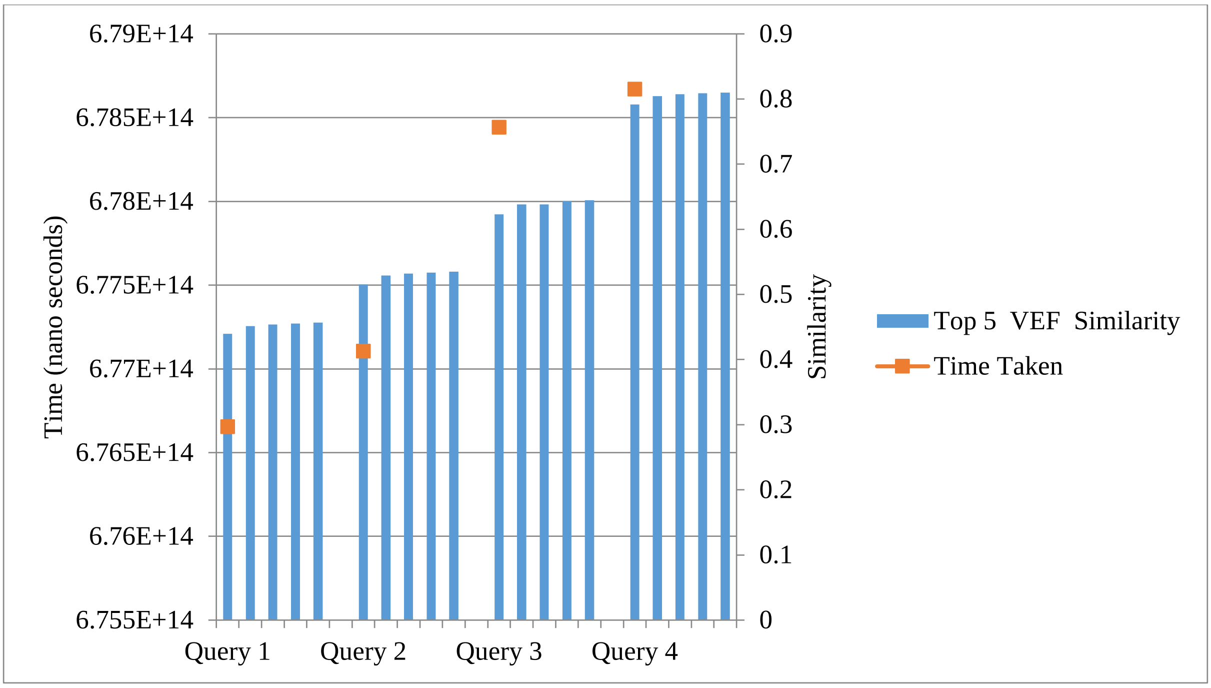

Figure 10 Calculating similarity for queries and corresponding time taken for query execution

3.1.3 *Analysing the change in similarity pattern with varying query input parameters*

The behaviour of the model was also analysed by executing queries having varying input variables (see Appendix Table 3). As discussed above, a similar pattern of the five most similar SOEKSs for each query was calculated as depicted in Figure 11. The similarity calculation was found to be quite accurate and the execution time of this set of queries was fairly short as well.

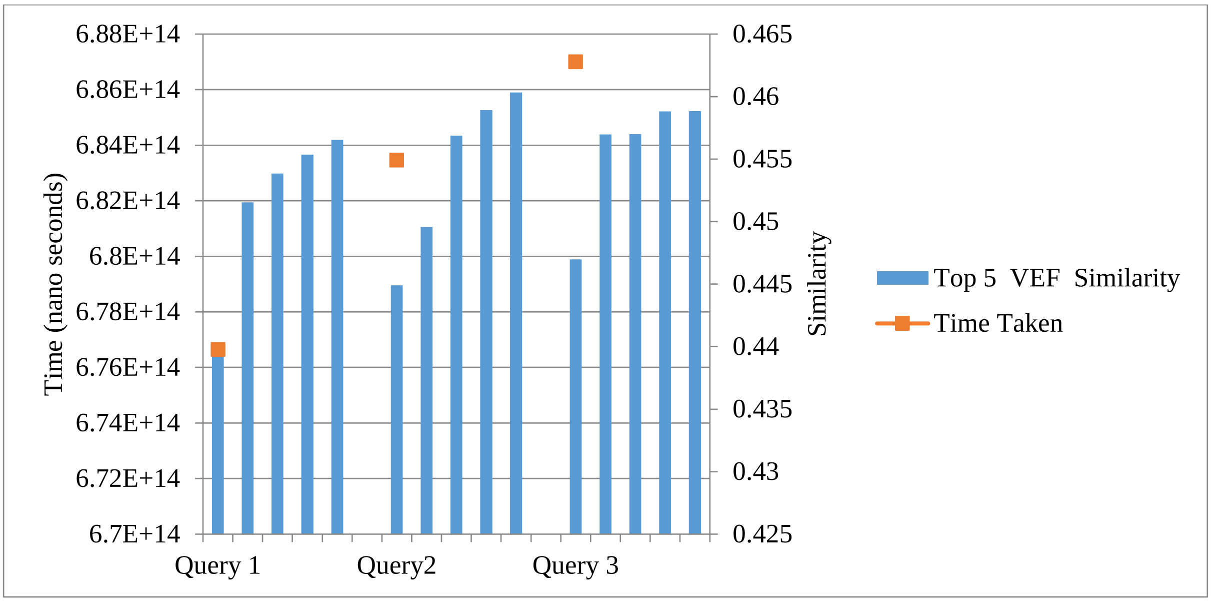

Figure 11 Similarity calculation for varying variable values

4 Conclusions and future work

The main contribution of this work is to demonstrate and implement knowledge based virtual engineering environment. The Manufacturing DNA which is the representation of manufacturing process collective computational intelligence is created by capturing experience of engineering objects, engineering processes, and factory and then using this information for the construction of Virtual Engineering Object, Virtual Engineering Process and Virtual Engineering Factory. The Set of Experience Knowledge Structure and Decisional DNA were applied as the knowledge representation structure for gathering the experience. Further, VEF-VEP-VEO were used as a tool for decision making processes that can enhance different manufacturing systems with predicting capabilities and facilitate knowledge engineering processes. Further, the VEO-VEP-VEF system readily copes with self-organizing production and control strategies; this is a significant example of linking product lifecycle management, industrial automation, and semantic technologies. The next step is to develop a network of manufacturing experience repositories by integrating diverse Manufacturing DNAs. The idea is to make experience shareable and transferable among different manufacturing set-ups as required by the future generation of cyber-physical systems.

Appendix

Table 1 SOEKS based Virtual Engineering Factory Structure

	Variables	Functions	Constraints	Rules
VEF-Loading/Unloading	vefCode_LU vepName vepCode_Exp Product Volume Amount Loading Period Station1 Loading Freq Unloading Freq Timing		vepCode_Exp ϵ vepDNA	
VEF-Transportation	vefCode_Trans vepName Priority vepCode_Exp AVG Distance Frequency No_Product Start Point End Point Route Pickup Priority		vepCode_Exp ϵ vepDNA AVG ϵ veoDNA	if Priority = Low, then pickup = FCFS if Priority = High, then pickup = FS
VEF-Storage	vefCode_Stor PartType vepCode_Exp Location Time_Storage Method Condition Quantity		vepCode_Exp ϵ vepDNA	if PartType = VEP, then StorageLocation = S1 if PartType = Tool and Die, then StorageLocation = S2 if PartType = Consumables, then StorageLocation = S3 if PartType = WIP, then StorageLocation = T1
VEF-QualityControl	vefCode_QC vepCode_Exp QC_Type Input I_QC Method Output O_QC Method			if QC_Type = Low, then O_QC Method = Manual if QC_Type = High, then O_QC Method = Machine
VEF-Experience	VEF_Code vepName vepCode_Exp Loading_Code Transportation_Code Storage_Code QualityControl_Code Total Machining Time Total Idle Time MakespanTime	$TotalMachiningTime = \sum_{veoCode=1}^{n}(\text{veoMachiningTime})$	vepCode_Exp ϵ vepDNA Loading_Code ϵ vefCode_LU Transportation_Code ϵ vefCode_Trans Storage_Code ϵ vefCode_Stor QualityControl_Code ϵ vefCode_QC	

Table 2 Set of queries with decreasing number of variables

	Input			Output							
Query#	Product	VEF Variables	VEF Variable Values	Top 5 VEF Similarity	VEF Code	VEP Code	VEO1 Code	VEO2 Code	VEO3 Code	VEO4 Code	Time Taken
1	Combustion Chamber	MST	528	0.439345102	24	24	434	114	397	1600	6.77E+14
		WIP	146	0.451549464	23	23					
		Total Machining Time	109	0.453842284	22	22					
		Total Idle Time	273	0.455370726	21	21					
				0.456546179	20	20					
2	Combustion Chamber	MST	528	0.51508188	24	24	1313	434	619	1591	6.77E+14
		WIP	146	0.529206153	23	23					
		Total Machining Time	109	0.531856754	22	22					
				0.533622089	21	21					
				0.534978474	20	20					
3	Combustion Chamber	MST	528	0.623123445	24	24	1313	434	619	1591	6.78E+14
		WIP	146	0.638332798	23	23					
				0.638332798	22	22					
				0.643085159	21	21					
				0.644543996	20	20					
4	Combustion Chamber	MST	528	0.79146728	24	24	1313	434	619	1591	6.79E+14
				0.80467767	23	23					
				0.807162215	22	22					
				0.808819983	21	21					
				0.810096086	20	20					

Table 3 Set of queries with the same number of variables with varying values

	Input			Output							
Query#	Product	VEF Variables	VEF Variable Values	Top 5 VEF Similarity	VEF Code	VEP Code	VEO1 Code	VEO2 Code	VEO3 Code	VEO4 Code	Time Taken
1	Combustion Chamber	MST	528	0.439345102	24	24	434	114	397	1600	6.77E+14
		WIP	146	0.451549464	23	23					
		Total Machining Time	109	0.453842284	22	22					
		Total Idle Time	273	0.455370726	21	21					
				0.456546179	20	20					
2	Combustion Chamber	MST	400	0.444905349	1	1	1313	434	619		6.83E+14
		WIP	100	0.449565847	2	2					
		Total Machining Time	55	0.456875457	3	3					
		Total Idle Time	250	0.458931983	4	4					
				0.46033116	5	5					
3	Combustion Chamber	MST	480	0.446987743	12	12	588	623	283	1071	6.87E+14
		WIP	122	0.456977656	13	13					
		Total Machining Time	97	0.456989075	11	11					
		Total Idle Time	161	0.458823166	14	14					
				0.458856013	10	10					

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