Smart Innovation Engineering: Towards Intelligent Industries of the Future

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Knowledge-based Engineering Systems are founded upon integration of knowledge into computer systems and are one of the core requirements for the future Industry 4.0. This paper presents a system called Smart Innovation Engineering (SIE) capable of facilitating product innovation process semi-automatically. It enhances decision-making processes by using the explicit knowledge of formal decision events. The SIE system carries the promise to support the innovation processes of manufactured products in a quick and efficient way. It stores and reuses past decisional events or sets of experiences related to innovation issues, which significantly enhances innovation progression. The analysis of basic concepts and implementation method proves that SIE system is an advanced form of Cyber Physical Systems. It is flexible, systematic, fast, and supports customization. It can play a vital role towards Industry 4.0 development.

Keywords: Smart Innovation Engineering, Product Innovation, Cyber Physical System, Industry 4.0, Set of Experience, Decisional DNA

Introduction

The process of product innovation is very difficult and complex as it requires comprehensive knowledge about new technological advancements, new materials, and knowledge of similar products having some common functions or features. Taking into account high customer expectation for quality products at lower costs and competition with other similar organizations, manufacturing units need to implement innovative changes in their products as regularly and as possible. They are also facing continuous market changes and need for shorter product life cycles (Verhagen, Bermell-Garcia et al. 2012). Other important factors, such as: technological advancements, development of better and cheaper materials with enhanced properties, improved/cost-effective manufacturing processes, and introduction of new/smart products into the market further intensify challenges faced by manufacturing units (Waris, Sanín et al. 2017). To survive in the current volatile market, companies around the world must continuously pursue product innovation (Chen and Feng 2009). Most manufacturing organizations put their customers' satisfaction on top priority to improve their competitiveness (Ai, Wang et al. 2013). Moreover, systematic and proper approach in product innovation can increase the life of the product.

Use of knowledge-based engineering (KBE) systems to cope with the process of product innovation is the need of an hour. KBE is a particular type of knowledge-based system (KBS) that is based upon the integration of Object-Oriented and Ontology-based programming, artificial intelligence (AI) and Computer-Aided Design (CAD) technologies (Pinfold and Chapman 2001, Pietranik and Nguyen 2015). A KBE is a system that uses artificial intelligence techniques in problem-solving processes to support human decision-making, learning, and action. One of the hallmarks of the KBE approach is to automate repetitive, non-creative design tasks. Apart from significant time and cost savings, automation also frees up time for creativity (Cooper and LaRocca 2007). Moreover, experience-based knowledge re-use guided by an established KBE framework has the potential to support the product innovation process.

The World is moving forward towards fourth industrial revolution that is known as Industry 4.0. The term Industry 4.0 is often understood as the application of the generic concept of Cyber Physical Systems (CPSs). CPSs refer to the next generation of engineered 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 (Duong, Nguyen et al. 2010).

Knowledge Engineering (KE) and Knowledge Management (KM) are important role players in cyber-physical systems. The concept of Virtual engineering object (VEO)

(Shafiq, Sanin et al. 2015, Shafiq, Sanin et al. 2016), an experience-based knowledge representation of engineering objects, can be treated as specific form of CPS and consequently can be utilized in design of Industry 4.0. The VEO concept was extended further into Smart Innovation Engineering (SIE) system by Waris, Sanin et al. 2016, and Waris, Sanín et al. 2017). The SIE system uses a collective, team-like knowledge developed by past experiences of the innovation-related formal decisional events. Through this systematic approach, product innovation process can be performed semi-automatically. Smart design and manufacturing systems capable of continuous design/innovation, configuration, monitoring and maintenance of operational capability, quality, and efficiency are, in fact, a requirement for the industry (Garcia-Crespo, Ruiz-Mezcua et al. 2010). According to the European commission under the Horizons 2020 program, the self-learning closing feedback loop between production and design should be included in future factories. The goal here is to show how SIE system can be considered as a step forward towards Industry 4.0.

Background

To clearly understand the SIE idea, some concepts are discussed in this section that throw some light on the technical aspects of the problem and are also helpful in justifying the assumed inter-relationship among these aspects.

Knowledge Engineering

Knowledge Engineering is an engineering discipline that aims to solve complex problems, normally requiring a high level of human expertise, by integrating knowledge into computer systems (Feigenbaum and McCorduck 1983). It involves the use and application of several computer science domains such as Artificial Intelligence (AI), Knowledge Representation (KR), databases and Decision Support Systems (DSSs). KE is primarily concerned with constructing a KBS. Knowledge engineers are interested in what technologies are needed to meet the enterprise’s KM needs. In developing KBS, the knowledge engineer must apply quality control and standards, plan and manage projects, and take into account technological, human, financial, and environmental constraints.

A KBS is a system that uses AI techniques in problem-solving processes to support human decision-making, learning, and action. Two central components of KBSs are:

- Knowledge base - consists of a set of facts and a set of rules, frames, or procedures.
- Inference engine - Responsible for the application of knowledge base to the problem on hand.

Some of the common types of KBSs are Expert systems, Neural networks, Case-based reasoning, Genetic algorithms and Intelligent agents. Knowledge acquisition is the process of acquiring knowledge from a human expert or a group of experts for the development of KBSs. It comprises a set of techniques and methods that attempt to elicit knowledge of a domain specialist through some form of direct interaction with the expert. Key issues associated with knowledge acquisition are:

- The end-product must be useful to the end-users
- To be useful, the end-product must be full of high-quality knowledge that is correct, complete, and relevant, and stored in a structured manner
- The project must be run in an efficient way making the most use of the available resources

Apart from that, the project should not unduly disrupt the normal running of the organization, hence should not involve too much time from experts.

Product Innovation

The key features for designing and manufacturing a new product are: required features/functions of the product, technology, resources and materials available, manufacturing processes, and other such factors at that time (Waris, Sanin et al. 2017, Waris, Sanín et al. 2017). For the prosperity and survival of the manufacturing unit in the highly competitive market, the entrepreneurs and manufacturing organizations have to introduce new features in their products, leading to innovation. They have to repeat the product innovation process after a particular time, otherwise their product may become obsolete.

In fact, the process of product innovation is very difficult and complex. Both knowledge and experience are essential attributes of an innovator that are necessary to find the best possible solution for the required changes that lead to innovation. These changes are based on the innovation objectives reapplied to the established, existing product. Product innovation process has to be quick and systematic so that the changes in the product may be implemented at the required time.

In the context of manufactured products, product innovation can be defined as the process of making required changes to the already established product by introducing something new that adds value to users, and also providing expertise knowledge that can be stored in the organization (O'Sullivan and Dooley 2008). Product innovation is about making changes to physical products. For example, adding functionality such as automatic locking system to automobiles, changing from old fuel injection system to multi-point fuel injection (MPFI) system, or introducing a new screen size in television sets. Innovation plays an important role in providing competitive advantage for manufacturing organizations (Gunday, Ulusoy et al. 2011). Strategy for implementation of product innovation includes the use of better components, new materials, advanced technologies, and new product features/functions. External factors such as legislation and sustainable development also affect implementation of product innovation. Another factor that is considered during product innovation process is ergonomics. Research suggests that ergonomics is related to product characteristics such as safety, efficiency of use, and comfort aimed at maximizing customer satisfaction (Oborne 1987). Ergonomic properties are recognized as important because firms are competing on ease of use of the product (Nussbaum 1993). Moreover, the establishment of cross-functional, multidisciplinary teams was found to be vital to the success of the innovation project (Jayaram, Okeb et al. 2014).

From the above discussion, it is clear that product innovation is a highly complex process that requires vast knowledge and other external factors. To address this problem we propose a system that uses a collective, team-like knowledge developed by experiences of the past decisions related to product innovation. This system is called SIE System (Waris, Sanín et al. 2017).

Industry 4.0 and Cyber Physical Production Systems

Systematic infusion of newest developments in computer science (CS), information and communication technology (ICT), and manufacturing science and technology (MST) into CPPS may lead to the fourth Industrial Revolution. The term "Industry 4.0" is used for the fourth industrial revolution which is to take place in not so distant future.

The concept of Industry 4.0 came into existence in 2011, when an association of representatives from academia, business, and politics promoted the idea as an approach for strengthening the competitiveness of the German manufacturing industry (Kagermann, Helbig et al. 2013). Industry 4.0 is a collective term for technologies and concepts of value chain organization. Industry 4.0 makes factories more intelligent, flexible, and dynamic by equipping manufacturing with autonomous systems, actors, and sensors (Roblek, Meško et al. 2016). Consequently, industries including smart products, machines and equipment will achieve high levels of automation and self-optimization. In addition, production of complex and customized products with high standards can be manufactured as per expectations. Thus, intelligent factories and smart manufacturing are the major goals of Industry 4.0 (Sanders, Elangeswaran et al. 2016). Cyber Physical Systems can be described as the transformative technologies for managing interconnected systems between its physical assets and computational capabilities, with the possibility of human machine interaction (Baheti and Gill 2011). CPSs has drawn a great deal of attention from academia, industry, and the government due to its potential benefits to society, economy, and the environment. Some of the practical examples in the present world are autonomous cars, robotic surgery, smart manufacturing, smart electric grid, implanted medical devises, and intelligent buildings. Application of CPS in the manufacturing industry leads to cyber-physical production systems (CPPS) and hence the ability for continuous viewing of product, production equipment and production system under consideration. The introduction of CPPS in any production system promises social, economic and even ecological benefits.

Due to the competitive nature of today's industry and recent development resulting in higher availability and affordability of computer networks, sensors and data acquisition, more and more industrial organizations are forced to move toward implementation of high-tech methodologies. Consequently, the ever growing use of networked machines and sensors has resulted in the continuous generation of high volume data which is known as Big Data (Lee, Lapira et al. 2013). In modern manufacturing organizations, especially high-tech industries, CPPS can be further developed for managing knowledge and experience in the form of Big Data and leveraging the interconnectivity of machines to reach the goal of intelligent factories. Furthermore, integrating CPPS with logistics and services in the current industrial practices would transform today's factories into an Industry 4.0 factory with significant economic potential (Lee, Lapira et al. 2013, Thiede, Juraschek et al. 2016).

Smart Innovation Engineering System

SIE system that is technically an extension of the work developed by Shafiq et al known as VEO which permits dual computerized/real-world representation of an engineering artefact (Shafiq, Sanin et al. 2016). VEO is a specialization of CPS in terms of its extension into knowledge gathering and reuse, whereas CPS is aimed only toward data and information management (Shafiq, Sanin et al. 2015).

The SIE system is a tool developed to support the innovation processes in a quick and efficient way. It stores the experiential knowledge of the past decisional events related to product innovation in the form of sets of experience and uses such experiential knowledge in decision making. Manufacturing organizations and entrepreneurs can take improved decisions systematically and at an appropriate time by implementing the SIE system in the process of product innovation. The SIE System is based on the Set of Experience Knowledge Structure (SOE) and Decisional DNA (DDNA), which were first presented by Sanin and Szczerbicki (Sanin and Szczerbicki 2004, 2005, 2007, 2008). It is a Smart Knowledge Management System (SKMS) capable of storing formal decision events explicitly (Sanin and Szczerbicki 2008a, Sanchez at al 2013).

The main three modules of SIE crucial for the purpose of innovation process are Systems, Usability, and Experience (Waris, Sanín et al. 2017):

Systems module represents knowledge about the relationships between various components (VEOs) at the same level or cross levels. This provides complete information about the logical relationships among the components and can be used to understand the genetic structure of the product including hierarchical decomposition and logical relationship of components.

Usability module represents the knowledge about the uses of a particular VEO in other products performing the same/similar function. This is very useful for calculating its performance in other products and finally its specific/overall performance. Other information like which products have stopped using the given component, its recent applications in other products, and the effect of inclusion of this component on the performance, popularity, sales or price of the other products is also included in this module. Usability module is especially useful when searching for alternative components that are used in various other products.

Experience module represents knowledge about the past innovation related events of the product. Every formal decision related to the product innovation is stored in this module.

Working Algorithm of SIE System

Each module of the SIE system creates Sets of Experience (SOE) that allows the experienced-based knowledge to be stored systematically for a wide range of manufactured products that are similar. Each SOE is a unique combination of variables, functions, constraints and rules, and the collection of them creates innovation related Decisional DNA that is integrated with the SIE system. In this way the SIE system represents complete knowledge and experience necessary to support innovation process of manufactured products.

As the decisional DNA is constructed in Java and has been successfully applied in various other fields of application, the code for SIE system was also written in Java programming language. The complete information about manufactured product is stored in each SIE module in Comma Separated Values (CSV) files. This information is in the form of sets of variable, functions, constraints and rules. A parser was written in Java to read these files. The parser reads variables, functions, constraints and rules from CSV files and “set of variables”, “set of functions”, “set of constraints” and “set of rules” are developed and combined together into one SOE. This is done for all CSV files in all modules of the SIE system. Each file represents a category of the SIE System and the collection of SOE of the same category forms a Chromosome of the system. Further collection of different Chromosomes (for each SIE module) forms what we call a Decisional DNA (DDNA) of the SIE System: SIE-DDNA.

Graphical User Interphase (GUI) for the SIE System is shown in Figure 1. This GUI allows the user to interact with SIE System in a user-friendly language. The user can select the set of values from the drop-down menu. This set of information (Query) is then converted into SOE and compared with the similar Sets of Experience that were generated by the SIE System from CSV files as explained above. The SIE System then compares the results of the most similar SOE and stores the changes that were made in those similar innovation precesses. These SOE actually represents the experiential knowledge of the successful changes made in product innovation processes of the group of similar products or products with similar features or objectives. Each past decision (SOE) has its Performance Factor (Waris, Sanín et al. 2017) that represents the success of the decision taken in that Product Innovation process. The SIE System looks for the best available option for a change that fits in the current Product (based on the constraints/preference set by the user).

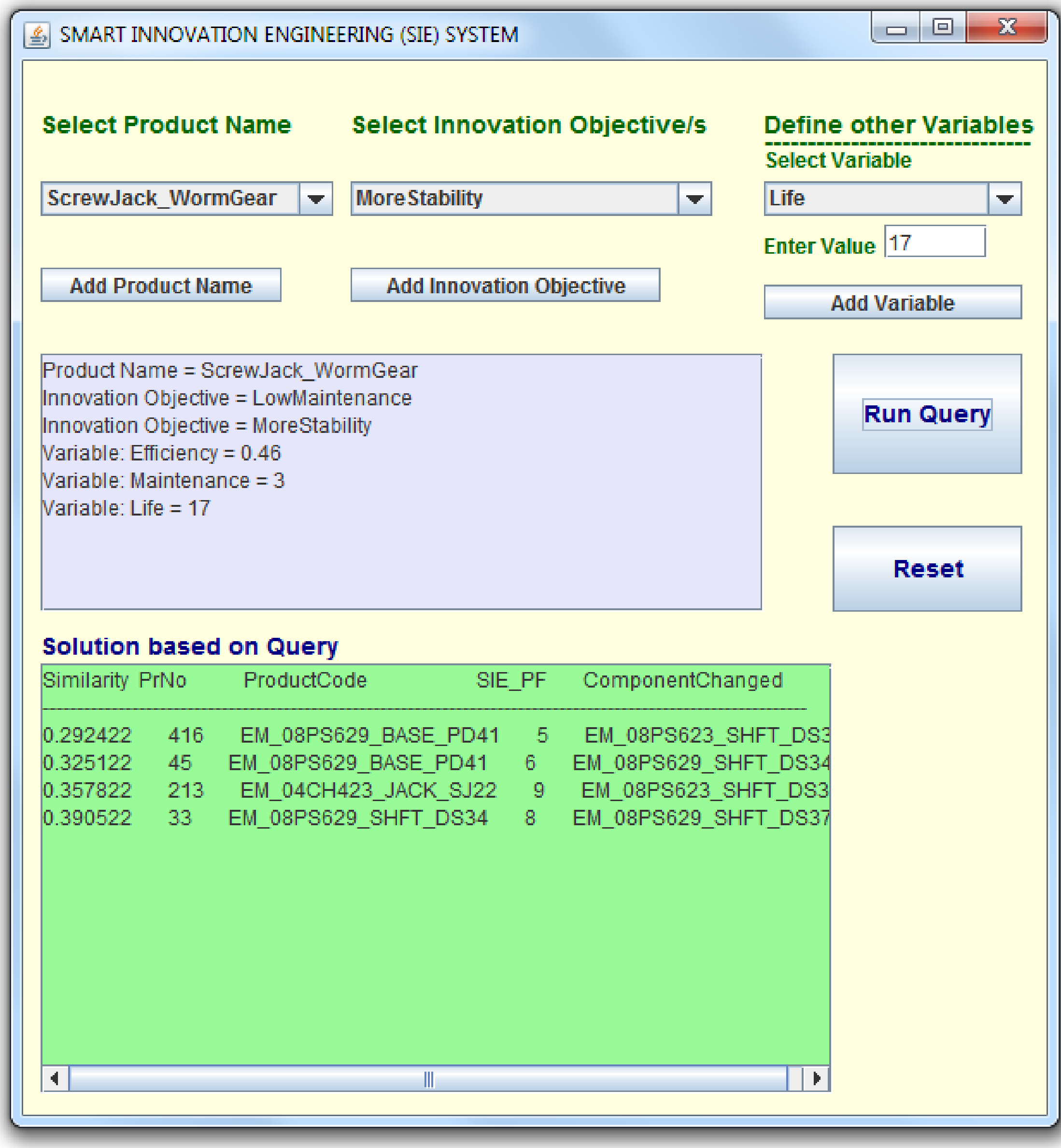

Figure 1. Graphical User Interface for SIE System.

The SIE System provide a list of proposed innovation solutions (say 5) that is displaced in the GUI (see Figure 1). At this time, the user/entrepreneur/innovator has the freedom to select the best possible solution from that list. This selection of solution completes the product innovation process and stores it in the SIE System as a new SOE. In this way, the SIE System gains experience with each decision taken which increases its expertise and behaves as an expert in its domain.

Results and Discussion

This SIE case study was carried out on a Dell laptop with Windows 7 Enterprise 64-bit operating system having Intel (R) Core (TM) i5-4210U CPU @ 1.70 GHz processor and 8 GB of RAM. The SIE-Decisional DNA consists of eight sets of experience from separate modules having a total of 74 variables, 6 functions and 31 constraints. For testing the working of SIE system, the sample query is obtained from a repository of 486 SOEs from all modules involved in SIE system. The GUI presented in Figure 1 for SIE is used to build innovation related queries. The user first selects the product undergoing innovation process from the 'Select Product Name' drop-down menu list. In this case study, the product is worm gear type screw jack. The user then adds the selected product to the query by clicking the 'Add Product Name' button, then selects the innovation objective required for innovation of worm gear type screw jack from the 'Select Innovation Objectives' drop-down menu list. After the user selects the first innovation objective and clicks the 'Add Innovation Objective' button, the selected innovation objective (low maintenance) is added to the query and displayed in the text-field as shown in Figure 1. Similarly, user can define more innovation objectives (more stability, in this case study) and add to the query. The user then defines the variables by selecting the variable from the 'Select Variable' drop-down menu list (under 'Define other Variables' label), type/assign the value of the variable in the text box next to 'Enter Value' label and clicks on the 'Add Variable' button to add the variable with the corresponding value to the query. In this way, user defines multiple variables with their values and adds them to the query and is also able to see the complete query in the text-field before execution to avoid any error. The typical query is shown below:

```
Product Name = ScrewJack_WormGear
Innovation Objective = LowMaintenance
Innovation Objective = MoreStability
Variable: Efficiency = 0.46
Variable: Maintenance = 3
Variable: Life = 17
```

Once the query is build, the user then executes the query by clicking the button 'Run Query'. In case of any wrong selection or mistyping, 'Reset' button is used to build the query again. The top 5 best matches are returned and displayed in the text-field below the 'Solution based on query' label as shown in Figure 1.

The process of searching similar SOE within the SIE-DDNA is executed 100 times with an average parsing time of 0.0211 seconds. The parsing time to identify each SOE and calculate similarity index is shown in Figure 2 for each iteration. Within one iteration, the average parsing time for each SOE is 0.0156 millisecond. Time taken by each of the 486 SOE to find the five most similar sets of experience is shown in Figure 3. This is considered an excellent time taking into consideration the large group of SOE and the number of comparisons performed within each SOE (comprising variables, functions and constraints) to calculate the five most similar SOEs to answer the input query.

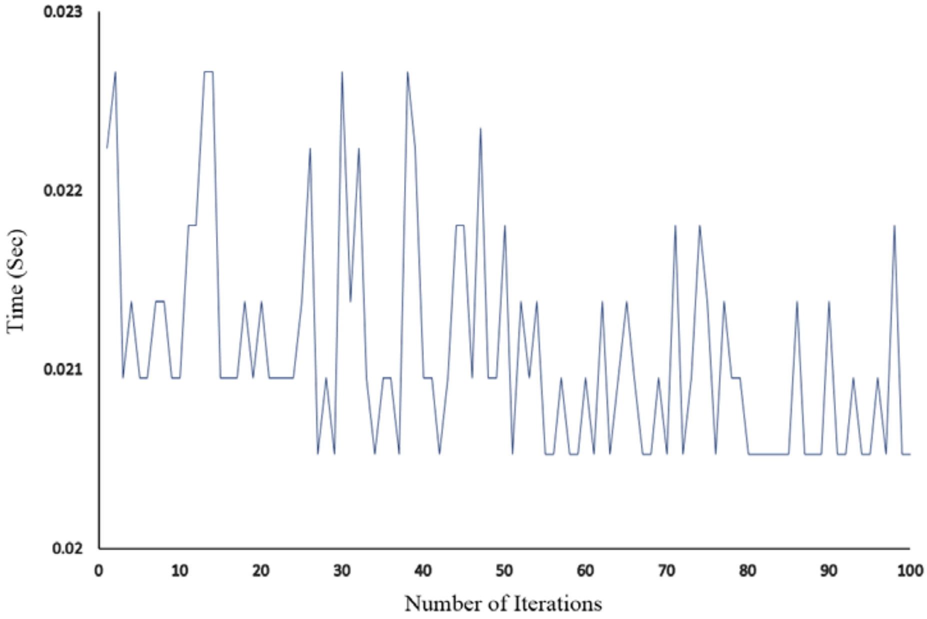

Figure 2. Parsing time for 100 SIE iterations.

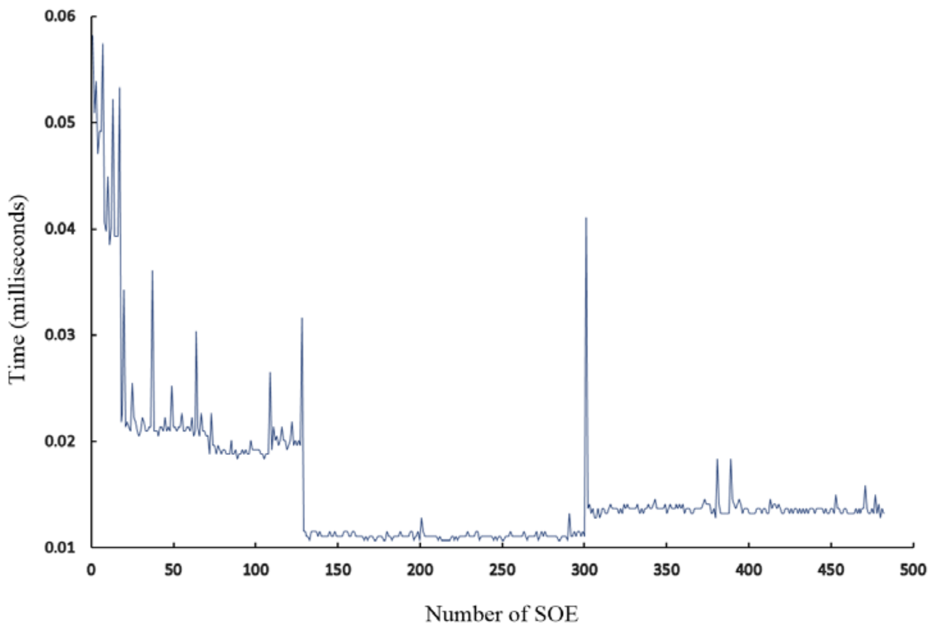

Figure 3. Parsing time for each SOE within SIE-DDNA.

The similarity of the input query with each of the 486 SOE within the SIE-DDNA is shown in Figure 4. The value of similarity varies from 0 to 1, with 0 being the closest and 1 meaning no similarity at all. Once the similarity for each SOE is calculated, the top similar SOE are sorted and stored.

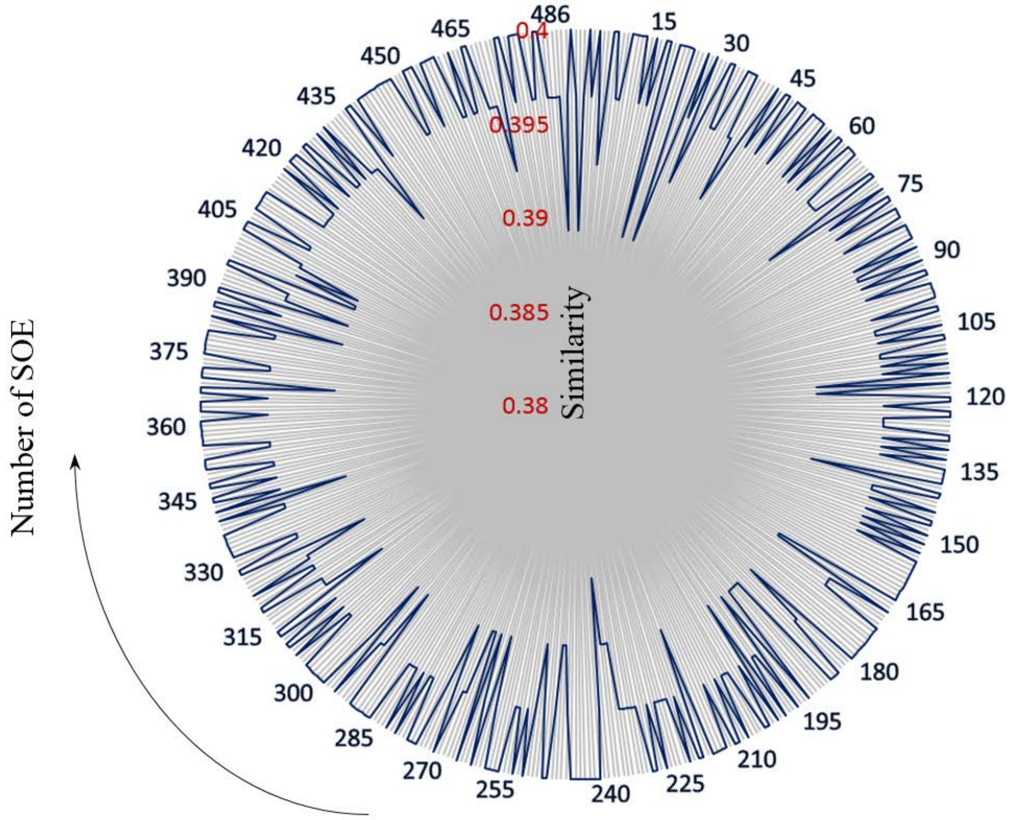

Figure 4. Similarity of input query with each SOE within SIE-DDNA.

Table 1 presents the list of sample input queries for the case study that were executed to find the most similar SOE. Consider for example Query 2 in Table 1. The similarity is calculated when the Product is ‘Screw Jack’, the innovation objectives are ‘Ease of operation’ and ‘Low Maintenance’ with variables: Efficiency = 0.47, Lubrication = SELF, Life = 16 and SIE_PF = 6. When this query is executed, SIE system returns the five most similar SOE. In this case, these are products with their product numbers (PrNo) 107, 266, 56, 479 and 457, having similarities equal to 0.389286, 0.389562, 0.391558, 0.392331 and 0.392331 respectively. The total time taken to execute this query is 0.017533 seconds.

Table 1. Solution to the random queries for case study.

Query No.	Input				Output			
	Product	**Innovation Objectives**	**Variables**	**Value of Variables**	**Top 5 SOE**	**Similarity (Top 5 SOE)**	**SIE _PF**	**Time taken**
					39	0.389286	5	0.015395
		EaseOfOperation	Efficiency	0.45	263	0.389286	5	
1	ScrewJack	MoreStability	Lubrication	YES	319	0.389562	6	
			Life	14	4	0.390854	9	
			SIE_PF	8	109	0.392857	9	
					107	0.389286	9	0.017533
		EaseOfOperation	Efficiency	0.47	266	0.389562	7	
2	ScrewJack	MoreStability	Lubrication	SELF	56	0.391558	7	
			Life	16	479	0.392331	7	
			SIE_PF	6	457	0.392331	9	
					4	0.389286	9	0.014968
		EaseOfOperation	Efficiency	0.45	425	0.389286	4	
3	ScrewJack	MoreStability	Lubrication	YES	263	0.392857	5	
			Life	17	319	0.392857	6	
			SIE_PF	5	109	0.392857	9	
					266	0.389542	7	0.015823
		EaseOfOperation	Efficiency	0.47	56	0.389542	7	
4	ScrewJack	MoreStability	Lubrication	NO	155	0.392857	5	
			Life	19	196	0.393120	3	
			SIE_PF	7	43	0.393120	8	

The five most similar SOE for all of the queries along with their similarities, performance factor and total time taken for execution are displaced in Table 1. To determine the performance and robustness of this model, a set of queries for product ‘Screw Jack’ and innovation objectives ‘Ease of operation’ and ‘More stability’ but with decreasing number of variables were executed as shown in Table 2.

Table 2. Solution to the queries with decreasing number of variables for case study.

Query No.	Input				Output			
	Product	Innovation Objectives	Variables	Value of Variables	Top 5 SOE	Similarity (Top 5 SOE)	SIE _PF	Time taken
					31	0.389286	5	0.017961
		EaseOfOperation	Efficiency	0.46	373	0.389286	5	
1	ScrewJack	MoreStability	Lubrication	SELF	233	0.392857	6	
			Life	15	311	0.392857	9	
			SIE_PF	7	143	0.392857	4	
					31	0.430556	5	0.015820
		EaseOfOperation	Efficiency	0.46	373	0.430556	5	
2	ScrewJack	MoreStability	Lubrication	SELF	233	0.435185	6	
			Life	15	311	0.435185	9	
					143	0.435185	4	
					373	0.481250	5	0.013257
		EaseOfOperation	Efficiency	0.46	233	0.487500	6	
3	ScrewJack	MoreStability	Lubrication	SELF	43	0.487500	8	
					96	0.487500	8	
					31	0.487500	5	
					373	0.544643	5	0.011119
		EaseOfOperation			233	0.553571	6	
4	ScrewJack	MoreStability	Efficiency	0.46	43	0.553571	8	
					96	0.553571	8	
					31	0.553571	5	

Figure 5 displays the execution time for two sets of input queries: one for the random queries having the same number of variables but different values, and the other for decreasing number of variables. It is clear from the figure that the execution time is less than 0.02 seconds which means the execution process is sufficiently fast. Figure 5 also shows that, as should be expected from the system, the time taken for execution decreases with decreasing number of variables.

Figure 6 displays the values of similarity of top five most similar SOE with respect to each query of two sets of input queries: one for the random queries having same number of variables but different values, and the other for decreasing number of variables. The similarity value increases as the number of variables of the input query decreases, the reason being lower number of the same/common variables. This further validates the efficiency of the SIE system.

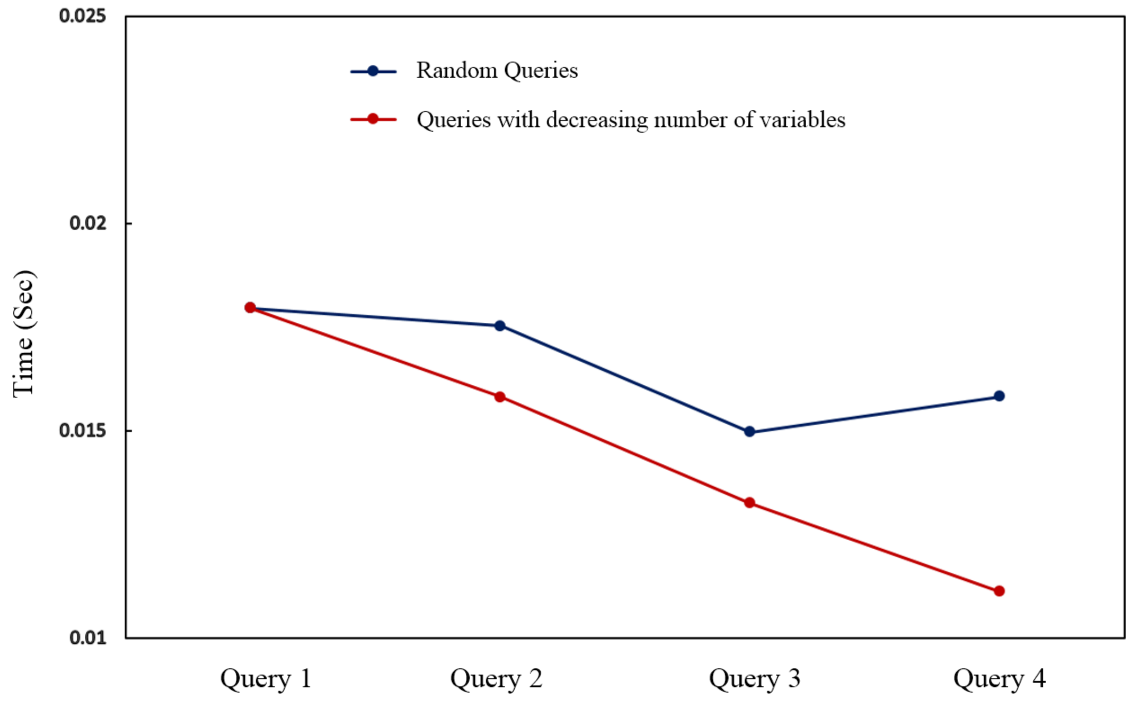

Figure 5. Time taken to execute different queries.

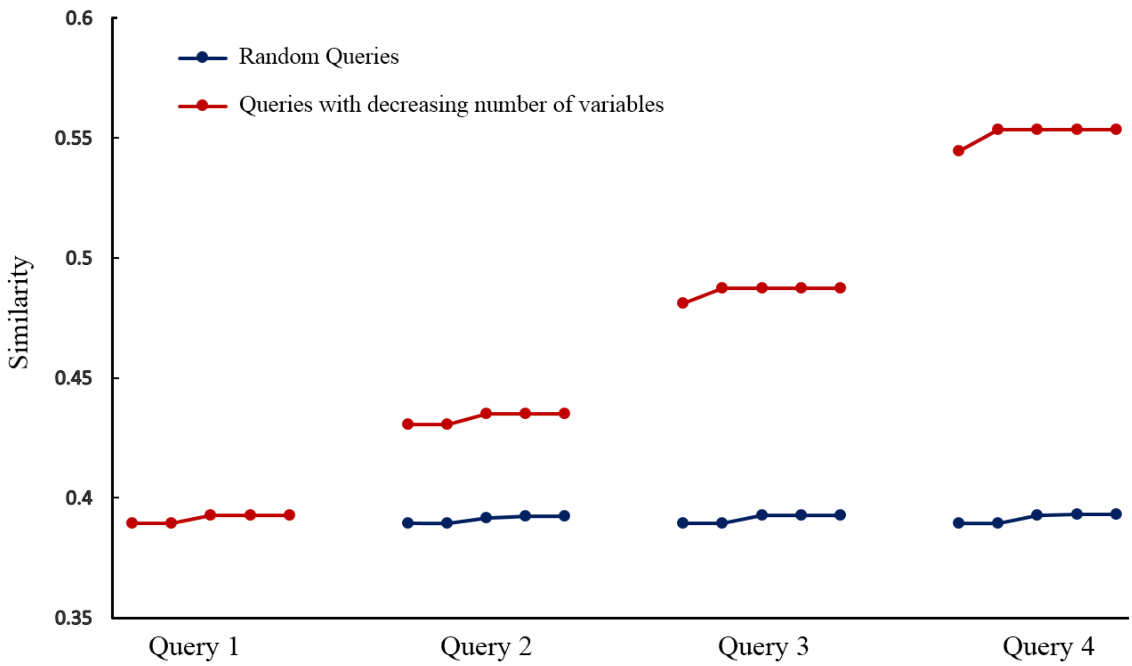

Figure 6. Similarity for different queries.

The presented case study was performed to practically:

- create SOE from the CSV files for different modules and calculate the time taken for creating each SOE,
- convert the input query into SOE and obtain five most similar SOE from the SOE of SIE-DDNA and calculate query execution time,
- analyse the changes in similarity patterns by varying the parameters of the input query and their values,
- confirm the execution time efficiency of the oresented SIE-DDNA system.

Conclusions

This paper presents the concept of Smart Innovation Engineering System that enhances the product innovation process. The importance of the SIE system can be justified from the point of view of potential benefits that it offers towards the establishment of Industry 4.0. Some of the advantages of the proposed system are as follows:

More flexibility: SIE system will allow manufacturing organizations to choose from the list of proposed solutions based on user preferences. Thus allowing the flexibility in product innovation process

Quick and systematic: Due to its fast computational capabilities, innovation process is much quicker as compared to the time taken by human group of experts. The process is systematic due to the fact that SIE system behaves as the group of experts that possesses comprehensive knowledge required for product innovation.

Customization: Industry 4.0 allows the incorporation of individual customer-specific criteria concerning design, configuration, ordering, planning, production and operation as well as enabling modifications to be made at short notice. Using SIE system will definitely help in achieving the design of customized products.

Reduction in costs: Implementation of SIE system in manufacturing industries will reduce their dependability on experts which will result in significant cost reduction in product innovation process.

The introduced SIE system is an advanced form of CPS and it can play a vital role not only in Industry 4.0 development, but also has the potential to be used further for lean innovation and sustainable innovation of the future.

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