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Experience-Based Product Inspection Planning for Industry 4.0

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Experience-Based Product Inspection Planning in Industry 4.0

Abstract:

In this paper we describe how our Smart Virtual Product Development (SVPD) system can be used to enhance product inspection planning. The SVPD system is comprised of three main modules, these being the design knowledge management (DKM) module, the manufacturing capability and process planning (MCAPP) module, and the product inspection planning (PIP) module. Experiential knowledge relating to formal decisional events is collected, stored and used by the system in the form of set of experiences (SOEs). Here we discuss the working mechanism of the PIP module and show how experiential knowledge relating to the inspection of products that have features and functions in common can be used to enhance product inspection planning during early stages of product development. Our discussion commences with an introduction to fundamental concepts and a general system overview. We then describe the development of our SVPD system's PIP module, and a case study we undertook for validation purposes. Results of the case study show that our system is capable of supporting product inspection planning in smart manufacturing, and thus has a vital role to play in Industry 4.0.

Keywords: Product development, Smart virtual product development system, Product inspection planning, Set of experience knowledge structure (SOEKS) and decisional DNA (DDNA), Metrology

1 Introduction and Background

Dimensional measurement plays a central role in enabling advanced manufacturing technologies by ensuring the quality of products and increasing the productivity of manufacturing organisations, and is crucial in the context of Industry 4.0, which requires reliable and accurate digital models of products, processes and production systems (Carmignato et al., 2020). It is performed by using an appropriate measuring instrument to measure the geometrical features of a part or product (Toteva and Vasileva, 2013) and is an important component of product inspection planning, which is an integral part of product design and manufacturing. Product inspection planning determines what characteristics of a product are to be inspected, and where and when inspection is to take place (Zhao et al., 2009). In order to guarantee the quality of both the product features and the processes used to manufacture the product, product inspection planning ensures that measurements are made at appropriate stages of the manufacturing processes to check that the work piece is not deviating from the shape specified by the design drawing (Badar et al., 2005, Whitehouse, 2010).

Among the things that distinguish advanced manufacturing from traditional manufacturing are higher levels of product customisation, tighter tolerances, and higher product qualities. The inspection of parts and assembled products has also evolved to support integrated manufacturing with the result that manufacturers can no longer rely on a one-dimensional approach in which they wait till the end of the manufacturing process before deciding whether to accept or reject an individual workpiece, and as such, companies have moved on to using multi-dimensional product inspection planning techniques. Such techniques involve the inspection of parts or products during prototyping as well as manufacturing (Zhao et al., 2009).

While the emergence of smart manufacturing has increased the variety and complexity of product lifecycle applications, it has also created challenges for manufacturing industries in the area of digital knowledge capture during product design, manufacturing, and inspection planning. Companies are in a race to gather, analyse and utilise data and knowledge related to product life cycle impact assessment, design improvement and quality assurance, however certain technical barriers prevent industries from utilizing knowledge related to product design and inspection during early stages of product development. The main obstacle is the lack of a well-accepted mechanism that would enable users to integrate data and knowledge (Feng et al., 2017a). The third industrial revolution has seen an increase in the capability, accuracy and complexity of measuring resources, and along with this has come automation and a need for updated inspection standards and advanced metrology equipment (Feng et al., 2017b).

The selection of any particular piece of measuring equipment or instrument is made based on the characteristics, tolerances, and datums of the part to be measured, and although it is an important aspect of quality control, very few techniques for the selection of dimensional metrology equipment are currently available (Toteva et al., 2014). In addition to this, the dawning of Industry 4.0 will see the transformation of conventional manufacturing to smart manufacturing, and whereas smart manufacturing opens the manufacturing loop by converting digital parts (drawings and models) into physical parts, product inspection closes this loop by using those physical parts to generate information and data i.e. product inspection / measurement reports (Moroni and Petrò, 2018).

These ongoing technological advances are having a significant influence on product design and manufacturing, with the selection of manufacturing equipment playing an ever more crucial role in the implementation of the cyber-physical production systems (CPPS) that promise to so significantly increase the flexibility and efficiency of manufacturing. Furthermore, new approaches to product inspection are required so as to ensure that standards of product quality can be maintained in these new cyber-physical environments (Anokhin and Anderl, 2019). The question of whether or not the inspection of a particular product or feature will be effective in ensuring adherence to required standards of quality depends on product inspection planning. If appropriate plans for product inspection have already been made at early stages of product development, then the potential for later mistakes can be diminished, and production costs can thus be kept under control (Moroni and Petrò 2018). The product inspection planning (PIP) module of the SVPD system, proposed by Ahmed et al. (Ahmed et al., 2020a, Bilal Ahmed et al., 2019), has been developed precisely to allow product developers to make product inspection plans at early stages of product development. The PIP module uses collaborative knowledge collected from relevant past product inspection experiences involving similar products or families of products.

The structure of this paper comprises of fundamental concepts in Section 2, which presents the basic concept of dimensional metrology and its importance along with product inspection planning, methods for selecting measuring equipment, and Set of experience knowledge structure (SOEKS) and Decisional DNA (DDNA). Overview of the SVPD system is described in Section 3, and implementation of the PIP module to enhance the product inspection planning is explained in Section 4. Results and discussion, and concluding remarks are presented in Section 5 and Section 6 respectively.

2 Fundamental Concepts

2.1 Introduction to metrology

Dimensional metrology is a science that involves the geometrical measurement of product features including length, area, volume, flatness, circularity, true position, perpendicularity, flatness, symmetry, straightness, concentricity, cylindricity, and parallelism among others (Leach and Smith, 2018, Ferrucci et al., 2018). It is synonymous with dimensional measurement and inspection in the literature. Dimensional metrology is essential for the correct manufacture of parts, and is based on complex 3D-geometric entries and the relationships between those entries. These geometric entries are associated with a large and diverse knowledge base that includes interconnections between measurement processes, measurement equipment, measurement management systems, traceability of equipment, and statistics (Zhao et al., 2011).

Dimensional metrology can be thought of as comprising four major interacting elements: product definition, measurement process planning, measurement process execution, analysis and reporting of the data (Proctor et al., 2007). In order to generate information that can support the development of a product inspection plan, it is very important to know which features need to be measured and which of the available measurement resources should be used (Zhao et al., 2011). Geometrical features can be measured using various measuring instruments and equipment. Included amongst these would be any type of hardware used in a measurement process, for example, coordinate measuring machines (CMM), vision inspection machines (VIM), fixtures, gauges, probes, probe extensions, styli, probe tips, vernier callipers, micrometres, dial indicators, scanners, laser trackers, and theodolites etc.. Among the gauges would be included such things as block gauges, height gauges, go/no-go gauges, depth gauges, and bore gauges (Toteva et al., 2014, Leach, 2011).

Dimensional metrology is also an important part of the post-manufacturing inspection of a manufactured workpiece. It is typically carried out in an environmentally-controlled metrology room and is done to ensure that the geometrical parameters of the workpiece meet design requirements for the purposes of quality inspection and control (Gao et al., 2019), however the role that metrology plays in quality control is not just restricted to workpieces. On-machine and in-process surface metrology is also used for the optimisation of manufacturing processes and machine tool settings. This is based on the fact that the quality of the product's surface texture reflects the characteristics of the manufacturing process. Surface form errors can be indicative of machine tool imperfections which can manifest as vibration, geometric error and thermal distortion (Whitehouse, 2010).

2.2 Importance of dimensional metrology and product inspection planning

Dimensional metrology has major applications in manufacturing, and in particular in workshops that produce mechanical parts. In the case of any product that is composed of multiple parts, dimensional metrology will have been applied to each part so as to ensure its compatibility and fit. The range of sizes and product types over which dimensional metrology is applied extends from the tiniest tracks on computer chips present in any smartphone or television, to aeroplane wings and wind turbines. Some specific examples of dimensional measurements required in precision industries include those crucial to the assembly and function of automotive components such as fuel injectors, and those relating to the displacement of a wafer support in a photolithography scanner (Ferrucci et al., 2018).

High productivity, flexibility, efficiency, product reliability and low scrap rates are important goals of modern manufacturing, which is also facing increasing pressure to reduce time to market. A number of methodologies have been proposed and implemented with a view to achieving these objectives. Many industrial products require optimisation with respect to key geometry-dependant characteristics (e.g. energy efficiency, manufacturability, wear, durability), and in this regard, geometrical metrology plays an essential role in the development of a comprehensive understanding of the geometry-based links that exist between the function, design and manufacture of an assembled product. When geometrical metrology is integrated into product and process development in an intelligent way, the result is more rapid optimisation of the product (Savio et al., 2016). An 'Inspection and test plan' (ITP) - also known as a 'Quality inspection plan' - lays out a schedule of inspections that are to be carried out at critical control points or holds within a process in order to verify that things are progressing in the way that they should be. Product inspection and test plans are often used so that the requirements of the ISO 9001 and other manufacturing standards relating to the control of production and service provision can be satisfied. Few of the important clauses of ISO 9001:2015, showing the importance of product inspection plans are shown in Figure 1 (Natarajan, 2017). The same principles apply to Industry 4.0, although the associated increased product diversity and sophistication has also resulted in a need for enhanced automated inspection planning and improved decision making in order that the close-fitting dimensions, tight tolerances, and required surface finishes can be achieved in the CPPS environment.

8.5.1 Control of production and service provision

"... c) the implementation of monitoring and measurement activities at appropriate stages to verify that criteria for control of processes or outputs, and acceptable criteria for products and services, have been met; ..."

8.6 Release of products and services

"The organization shall implement planned arrangements, at appropriate stages, to verify that the product and service requirements have been met. ... "

Figure 1: Clauses from ISO9001:2015, showing the importance of product inspection plans.

2.3 Methods for selecting measuring instruments

The selection of appropriate measuring instruments is one of the most important aspects of the process of measurement, and as such careful attention should be paid to this when generating product inspection plans. When selecting measuring instruments, many complexities such as the size and geometry of the feature, and the relevant tolerances and datum must be taken into account (Feng et al., 2017b). In single production companies the dimensional control of workpieces in manufacturing can be achieved by use of universal measuring equipment (callipers, micrometres, indicating internal gages etc.), while for serial production the main measurement testing and control instruments are limit gauges, measurement templates and semiautomatic measurement instruments (Toteva et al., 2014).

2.4 Set of experience knowledge structure (SOEKS) and Decisional DNA (DDNA)

Set of experience knowledge structure (SOEKS) are able to store formal decisional events in an explicit manner (Sanin and Szczerbicki, 2009, Sanin and Szczerbicki, 2004). Generally speaking, SOEKS is a smart knowledge-based decision support tool which stores, shares, and maintains experiential knowledge, which can then be used for the enhancement of future decision-making whenever a new query is generated or presented.

A Set of Experience (SOE, a shortened form of SOEKS) is comprised of four basic components, these being variables (V), functions (F), constraints (C) and rules (R) (see Figure 2).

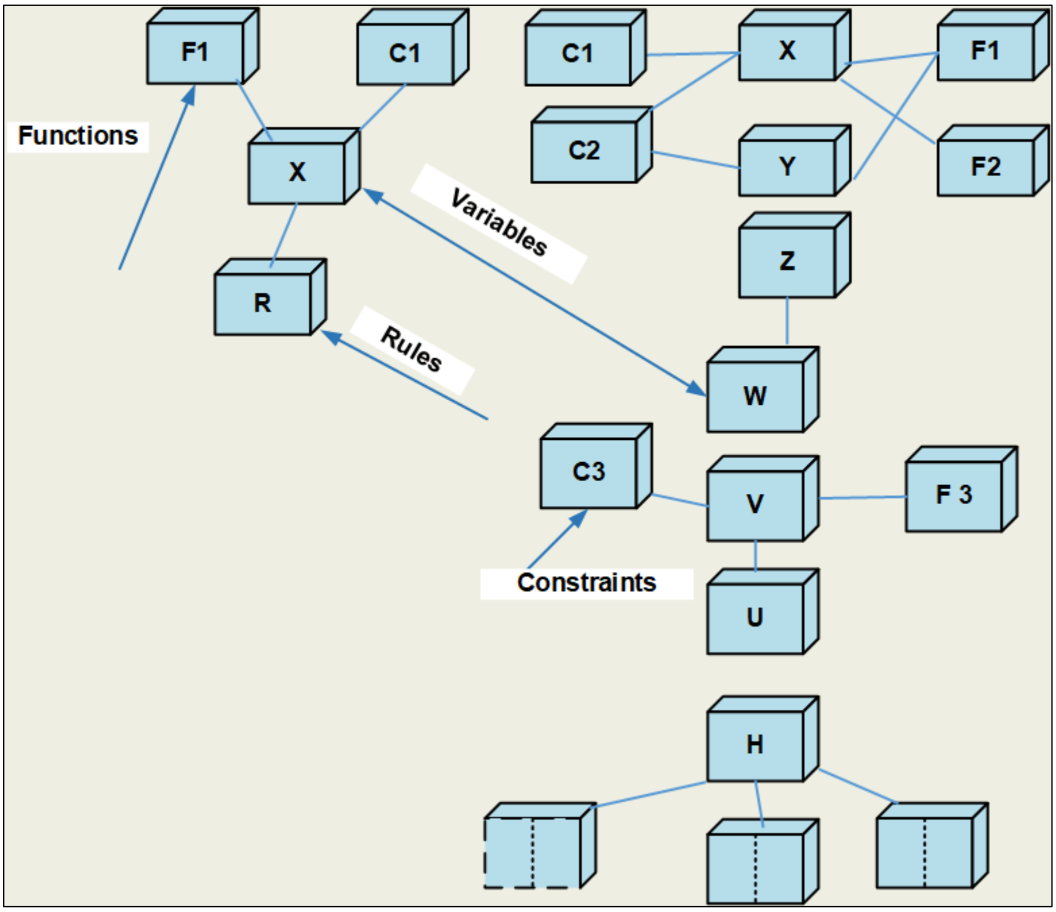

Figure 2: A three-dimensional view of a Set of Experience (SOE).

The variables define the functions, while the functions create the relationships between the variables, with both of these then being used to develop multi-objective goals. The constraints are also functions, and they are applied by the SOEs in order to obtain feasible solutions, and to control the system's performance with respect to defined goals. Rules, on the other hand, represent the conditional relationships between the variables, and are defined in terms of IF-THEN-ELSE logical statements. Any particular formal decisional event can be represented within the SOE by a unique combination of these variables, functions, constraints, and rules. Groups of SOEs form 'chromosomes'. Each chromosome contains all the SOEs related to a specific area/domain within the organization, and stores decisional strategies related to a given domain. The entirety of an organisation's precisely structured and grouped sets of chromosomes is known collectively as the organisation's Decisional DNA (Sanin and Szczerbicki, 2004).

The term 'Decisional DNA' comes from the idea that SOEs and their related structures possess features that are in some ways analogous to those of biological DNA. For example, just as the uniqueness of a particular piece of DNA is dependent upon its particular combination of the four nucleotides Adenine, Thymine, Guanine, and Cytosine, so the uniqueness of a particular SOE derives from its particular combination of variables, function, constraints, and rules (Sanin and Szczerbicki, 2009). SOEKS and DDNA are already being applied successfully in various fields, including in those related to industrial maintenance, in the semantic enhancement of virtual engineering applications, in state-of-the-art digital control systems involved in the production of geothermal and renewable energy, in the storage of information and periodic decision-making in banking and supervision, in the e-decisional community, in virtual organization, in interactive TV, and in decision-support medical systems (Shafiq et al., 2014).

3 Overview of the Smart Virtual Product Development System

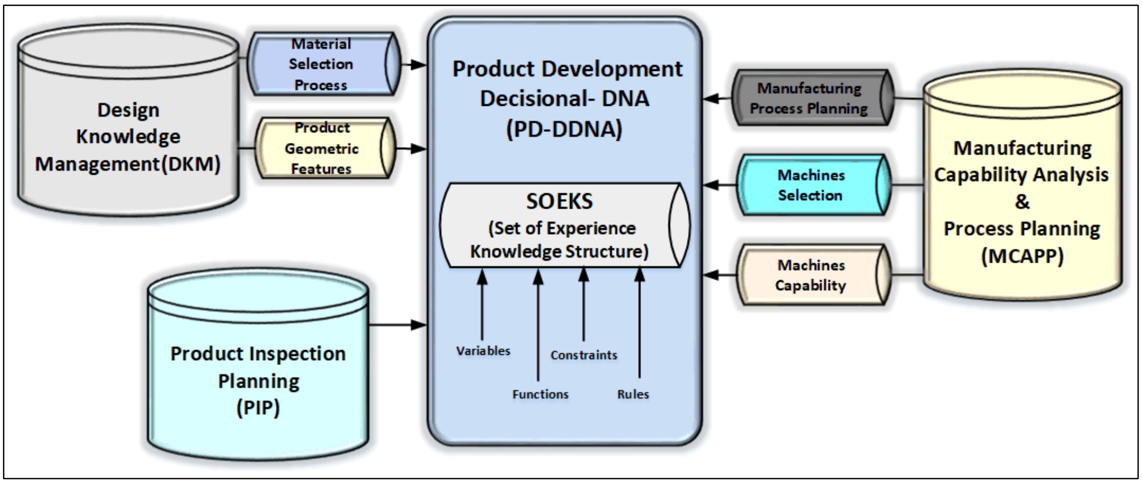

Figure 3: Architecture of SVPD system.

The Smart Virtual Product Development (SVPD) system is a decisional support tool for industrial product development processes. It stores, uses and shares the experiential knowledge of past decisional events in the form of set of experiences (SOEs). It has been developed to address a need for digital knowledge capture in the areas of product design, manufacturing, and inspection planning in smart manufacturing, and will bring about the improvements in product quality and development times that will be required from an Industry 4.0 perspective. The architecture for our SVPD system is given in Figure 3. The system consists of three modules, these being the design knowledge management (DKM) module, manufacturing capability analysis and process planning (MCAPP) module, and product inspection planning (PIP) module (Ahmed et al., 2020a, Ahmed et al., 2019, Bilal Ahmed et al., 2019).

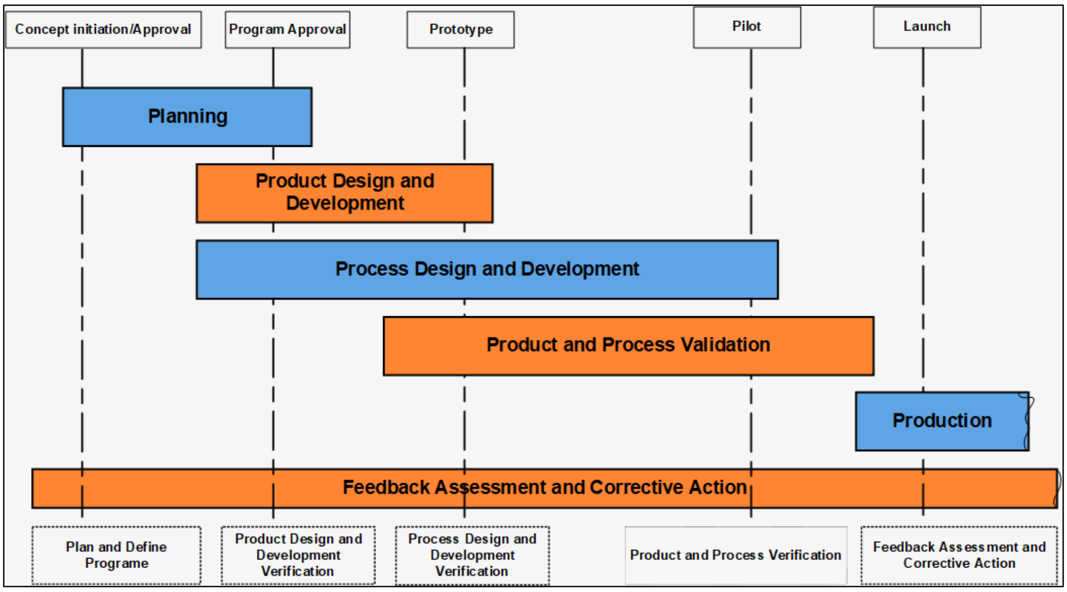

Figure 4: The various phases of advance product quality planning (APQP) methodology.

These modules interact with the system's DDNA knowledge repository, in which is held experiential knowledge acquired from previous projects. Integrated SVPD modules are able to provide confirmation that the processes involved in the production of a given product are ecologically sustainable, and can be undertaken in an existing facility. These modules are also fully capable of supporting the five phases of Advance Product Quality Planning (APQP) methodology, which is a framework for developing products or services that are able to satisfy customer requirements, and has been widely used in the aerospace, automobile, and medical device manufacturing industries. The five phases of APQP are shown in Figure 4 (Stamatis, 2001, Stamatis, 2018). Working mechanism of DKM module and MCAPP module was presented in our previous works (Ahmed et al., 2020a, Ahmed et al., 2019, Bilal Ahmed et al., 2019), this research presents the working algorithm of PIP module of the developed system.

4 Implementation of the Product Inspection Planning (PIP) Module

The product inspection planning (PIP) module is the third and last module of the SVPD system. It is used to identify which of the geometric features of a workpiece should be inspected during manufacturing, and is used also for the selection of measuring instruments or equipment most appropriate to those inspection tasks. In our previous work (Ahmed et al., 2018), we introduced a case study involving the design and development of a threading tap, which we undertook in order to validate all modules of the SVPD system. In this research we describe this case study in more detail, and in particular with respect to the validation of the development of PIP module. The first step in our discussion of the SVPD system thus far involved using the DKM module to select the appropriate material and to create geometric features. This was then followed by use of MCAPP module to generate the manufacturing processes and for selection of machines suitable for these processes. In the next step of the SVPD system, the solutions to queries built using these first two modules will now be used as input to build queries for the PIP module.

4.1 Working algorithm of the PIP module

In this section we describe the working algorithm of the PIP module of SVPD system, as it applies to the generation of a product inspection plan for our case study involving a threading tap. Once the important variables involved in the product inspection planning of the threading tap family of products have been manually generated as SOEs and saved in a comma-separated values (CSV) file, weighting is assigned to each of the characteristics of the variables (Ahmed et al., 2020b). For illustrative purposes a portion of the CSV file for the product inspection planning for threading taps is shown in Appendix-1. Because the DDNA and first two modules of the SVPD system had been developed in JAVA, we chose JAVA also when writing the parser (pipParserCSV) for the PIP module. The working procedure for the PIP module is as follows:

- User provides input query in terms of variables, functions, and constraints. This query is converted into a new SOE i.e. Query SOE.
- The parser then looks for the term ‘Variables’ and goes to the next line. The first line after the term ‘Variables’ contains the name of variables. It stores values written in each cell of the first line as the ‘Name’ of the variables. Each line after this contains the values of corresponding variables. The parser assigns values to the respective variables. This group of variables is stored in the system as one ‘Set of Variables’.
- Similarly, the parser reads the second set of values from the CSV file and assigns them to the respective variables which are stored as the second ‘Set of Variables’.
- The same process continues until the parser finds the term ‘Functions’, ‘Constraints’, or ‘Rules’. In the same way, the parser reads ‘Set of Functions’, ‘Set of Constraints’, and ‘Set of Rules’ from the CSV file.
- One ‘Set of variables’ plus ‘Set of Functions’, ‘Set of Constraints’, and ‘Set of Rules’ are combined together to form SOEKS.
    - *SOEKS = Variable set + Function set + Constraint set + Rule set*
- System finds the similarity of Query SOE with SOEKS stored in the CSV file. Similarity is calculated on the basis of Euclidian distance with its value ranging from 0 to 1 (0 being the closest).

- System provides output in the form of top five proposed solutions with minimum similarity and user then selects the best solution.

4.2 Graphical user interface for the PIP module

The graphical user interface (GUI) for the SVPD system is shown in Figure 5. After logging in, the user is prompted to make a selection from among the system's three main modules. After selection of the PIP module, the user selects the product to be manufactured (in this case 'Threading Tap') from the 'Select Product' dropdown, and then clicks the 'Add Product' button. Next, the user selects the material from the list provided in the 'Select Material' dropdown (see Figure 5), enters the relevant code into the text box below, and then clicks the 'Add Material' button.

Following this, the user selects the required machining operation from the 'Select Machining Operation' dropdown, enters the relevant workstation number into the text box below, and clicks the 'Add Operation' button. The selection of critical variables then proceeds in a similar way, whereby the user selects the required critical variable from a dropdown, enters the variable value into the textbox below, and then clicks the 'Add Variable' button. Multiple variables can be selected and added in this way. After the product, material, machining operation and critical variables selections have been made, they appear below in the 'Built Query' section of the screen (see Figure 5). An example of a possible random query is shown below.

- *Product Name = Threading Tap*
- *High speed steel (HSS) = T11301*
- *Thread grinding = 09*
- *Variable length = 40*
- *Variable diameter = 10*
- *Variable true position of hole = 0.03*

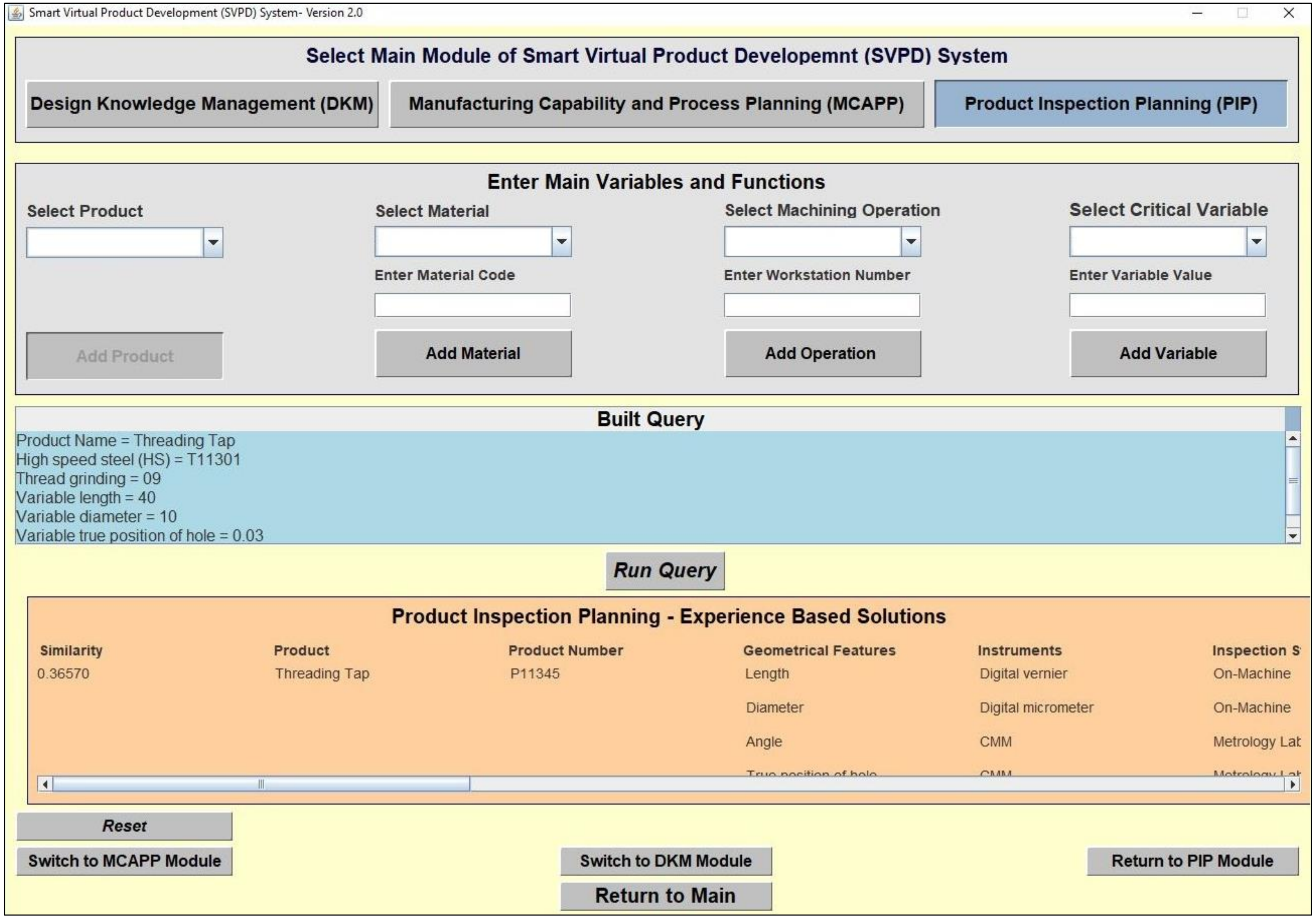

Figure 5: GUI for building queries for the PIP module.

Once the query has been built, the user then executes it by clicking the 'Run Query' button. This prompts the algorithm to retrieve the five closest matches, and these then appear as SOEs in the 'Product Inspection Planning – Experience Based Solutions' text-field below. These SOEs contain output including the similarity of the query SOE to the output SOE, the product name, the product number, the geometrical features to be measured, the instruments or equipment required to measure those features, the instrument IDs and the inspection stations. A number of other buttons can be seen at the bottom of the GUI screen. These include the 'Reset' button, which can be used to rebuild a query before or after it has been executed if any selection or typing errors have occurred, and other buttons which allow the user to switch between modules or to return to the main screen. As with the DKM and MCAPP modules, matching between the query SOE_j (a SOE made up of the query) and the SOE $pipDNA_i$ (the entire PIP-DNA) is made through calculation of a similarity index based on Euclidean distance. In this regard, the PIP similarity matrix takes the following form:

$$S_v(pipDNA_i, QuerySOE_j) = \sum_{k=1}^{n} w_k \left[\frac{\left| pipDNA_{ik}^2 - QuerySOE_{jk}^2 \right|}{\max\left(|pipDNA_{ik}|, |QuerySOE_{jk}| \right)^2} \right]^{0.5} \forall k \in pipDNA_i \wedge QuerySOE_j \quad (1)$$

5 Result and Discussion

The case study for the PIP module was executed on a Dell laptop running a Windows 10 Enterprise 64-bit operating system with an Intel ® Core ™ I5-7300u CPU @ 2.60 and 8 GB of RAM. The working algorithm of the PIP module was tested by directing sample queries towards a repository consisting of 500 set of experiences made up of 7 functions and 21 constraints. Each SOE within the repository was comprised of 7 variables. The following provides a general analysis of a case study undertaken to check the robustness of the system.

5.1 Parsing time for CSV file and SOEKS elements of the PIP module

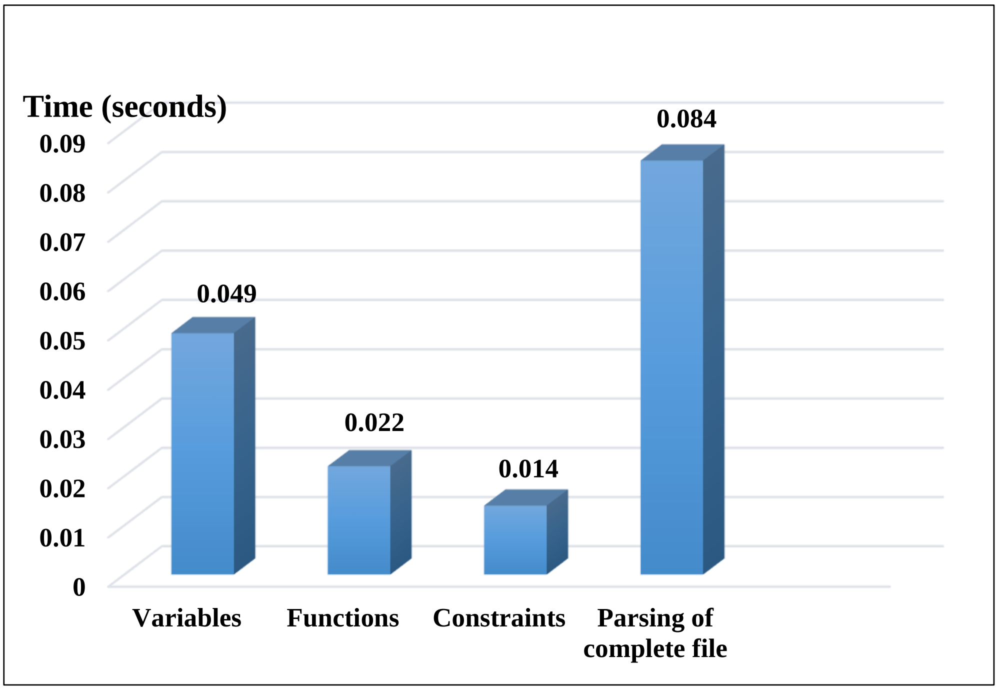

Figure 6: Parsing time vs SOE elements for the PIP module.

As shown in Figure 6, the average parsing time for a CSV file by the PIP module was 0.084 seconds, which can be considered to be a good result when the complexity of the SOEs with their large numbers of variables, functions and constraints is taken into account. Where the various SOE elements are concerned, parsing times were 0.049 seconds for variables, 0.022 seconds for functions and 0.014 seconds for constraints.

5.2 Time required for SOE searches within PIP module

The time for an SOE search within the PIP module was determined by averaging the times taken for each of 100 searches. This yielded an average parsing time of 0.02309 seconds, as shown in Figure 7.

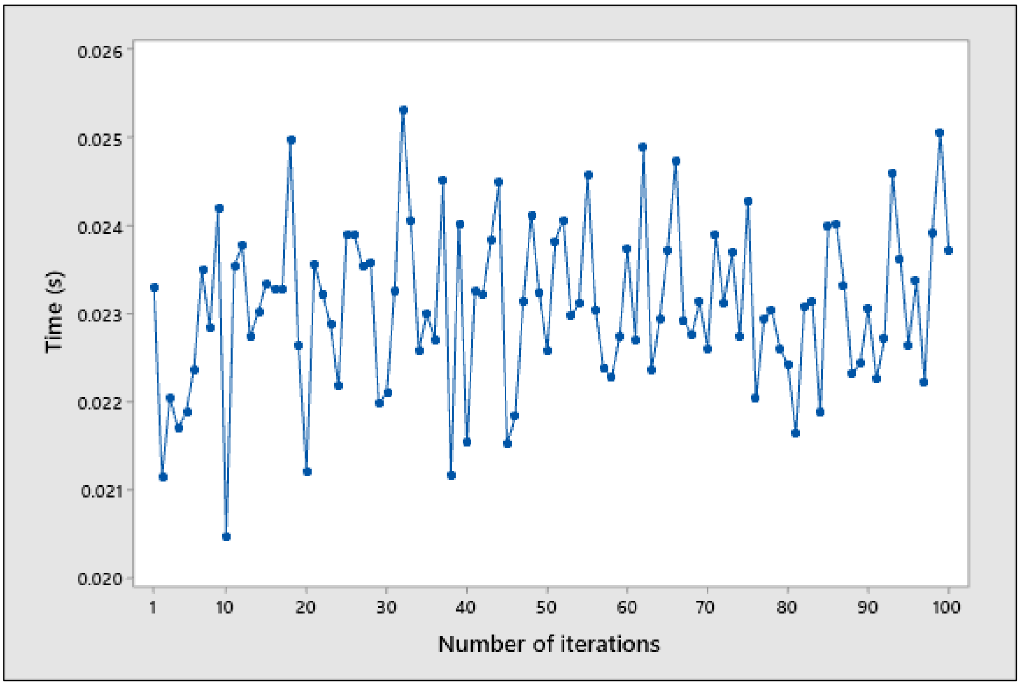

Figure 7: Time required for SOE searches within the PIP module

5.3 Normality test for SOE search data

The normality of the data (time) to search SOE within the PIP module was assessed using the Anderson-Darling test. This statistical test provides a measurement of how well a specified data set fits a particular type of distribution. When using Anderson-Darling, a determination of whether or not the data set fits the distribution type is based on the p-value yielded by the test (Fitrianto and Chin, 2016). The hypotheses for the Anderson-Darling test are:

- H0: The data follow a specified distribution
- H1: The data do not follow a specified distribution

If the p-value is less than a chosen alpha (usually 0.05 or 0.10), then the null hypothesis that the data follows a particular distribution type is rejected. We chose a p-value of 0.10 as the basis on which to accept or reject the null hypothesis that our data is normally distributed. From Figure 8, we can see that the p-value for our 100 PIP module searches was less than 0.10 (our chosen p-value) and so we accept that our data is normally distributed and that our search results are consistent.

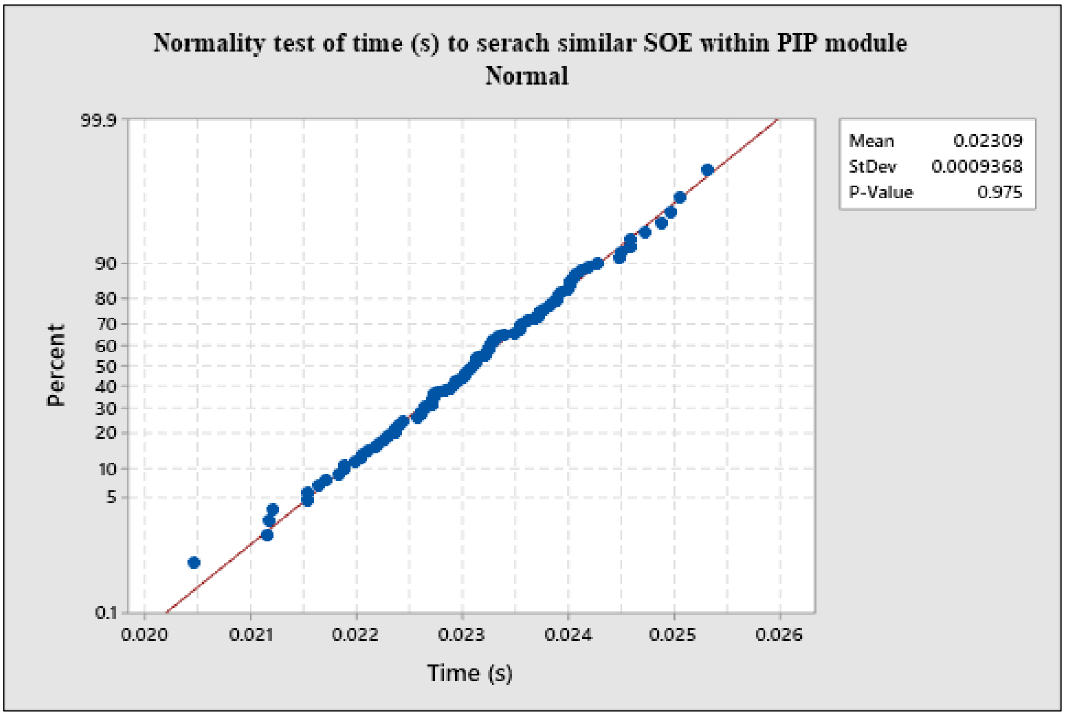

Figure 8: Normality test of time (s) for searches within the PIP module.

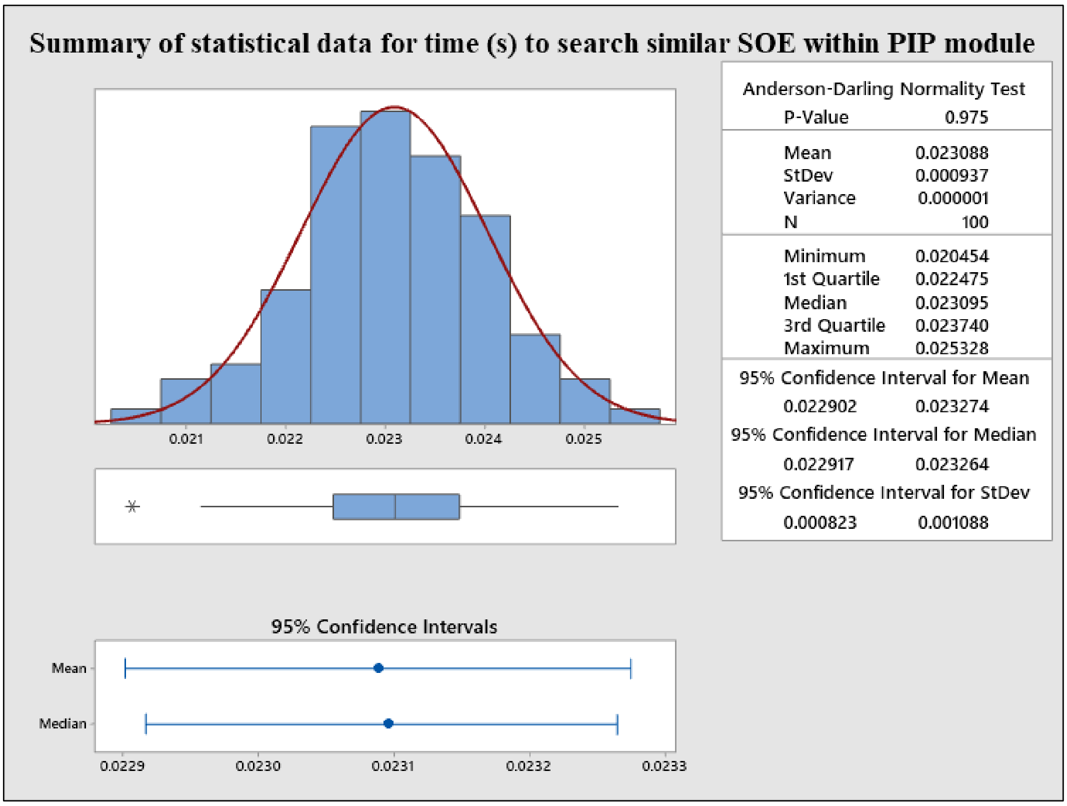

Figure 9: Statistical summary report for data to search similar SOEs within the PIP module.

A summary of the statistical data is given in Figure 9 where the p-value, mean, standard deviation, median, variance, and result minimum and maximum can be seen.

5.4 *Similarity calculation for 100 SOEKS stored in PIP module*

Similarity values for 100 SOEKS stored in the PIP module that were retrieved using random queries are shown in Figure 7.

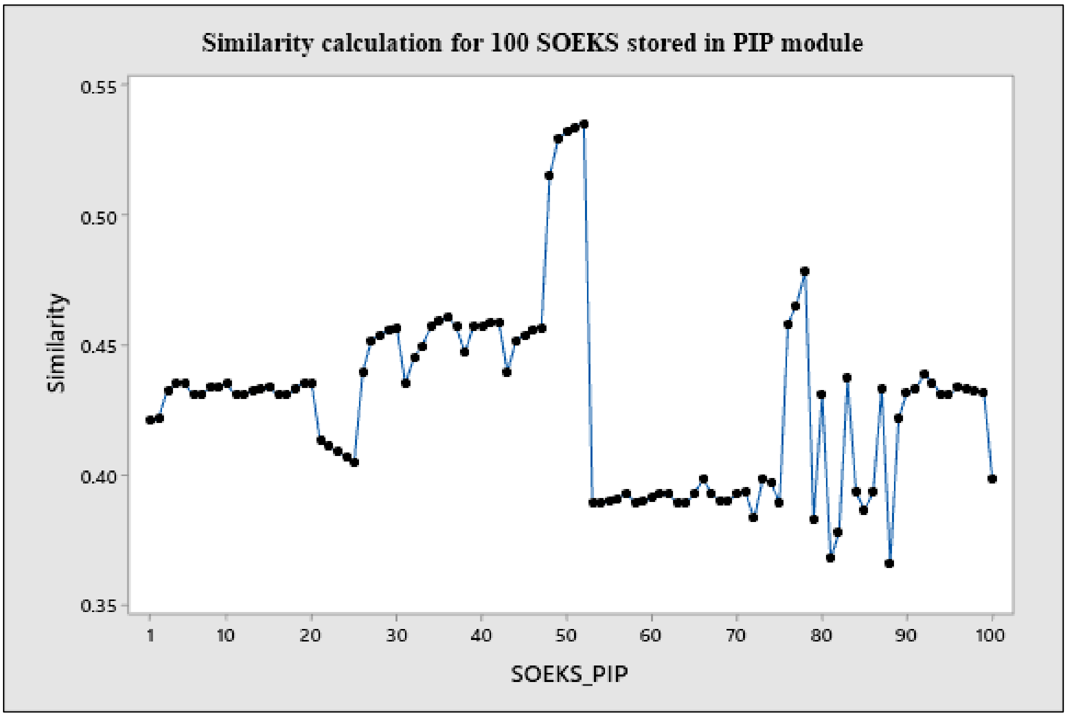

Figure 10: Similarity calculation for SOEKS stored in the PIP module.

6 Conclusion

In this study, we presented the concept of enhancing the product development process by providing product inspection planning knowledge during early stages of product development. We were able to achieve this enhancement by using our SVPD system's PIP module, which we validated using a case study involving a threading tap. Results from the case study indicate that our system is capable of enhancing the product inspection planning by using the previously acquired experiential knowledge of similar products.

The PIP module of the system can be used to generate product inspection plans for newly developed products. After a query based on specific objectives is fed into the system, the system's DDNA retrieves suitable solutions based on a set of priorities and constraints. Following execution of the query, the user selects the most appropriate solution from among those provided, with this then being stored in in the DDNA of the system as new experiential knowledge which then can be used for solving similar queries in the future. The integration of our system with ERP systems such as SAP or Oracle discrete manufacturing will lead to more enhanced decision-making in relation to product inspection planning in the future.

Appendix 1: CSV file component for PIP module.

Variables							
Product_Name	Material_type	Material_code	Machining_operation	Geometrical_feature	Instrument	Instrument_ID	Inspection_station
Threading Tap	HSS	T11307	Laser Cutting	Length	Vernier	I123470	On-Machine
Threading Tap	HSS	T11302	CNC Turning	Diameters	Micrometer	I123471	On-Machine
Threading Tap	SHS	T12001	CNC Milling	Angles	CMM	I123472	Metrology lab
Threading Tap	SHS	T12002	Heat Treatment	Hardness	Hardness Tester	I123473	Mechanical Lab
Threading Tap	SHS	T12003	Thread Grinding	Minor Diameter	Vision inspection	I123474	Metrology Lab
Threading Tap	HSS	T11308	Laser Cutting	Length	Vernier	I123470	On-Machine
Threading Tap	HSS	T11306	CNC Turning	Diameters	Micrometer	I123471	On-Machine
Threading Tap	SHS	T12005	CNC Milling	Angles	CMM	I123472	Metrology lab
Threading Tap	SHS	T12006	Heat Treatment	Hardness	Hardness Tester	I123473	Mechanical Lab
Threading Tap	SHS	T12004	Thread Grinding	Pitch of thread	Vision inspection	I123474	Metrology Lab
Threading Tap	HSS	T11309	Laser Cutting	Length	Vernier	I123470	On-Machine
Threading Tap	HSS	T11312	CNC Turning	Diameters	Micrometer	I123471	On-Machine
Threading Tap	SHS	T12007	CNC Milling	Angles	CMM	I123472	Metrology lab
Threading Tap	SHS	T12009	Heat Treatment	Hardness	Hardness Tester	I123473	Mechanical Lab
Threading Tap	HSS	T13009	Thread Grinding	Minor Diameter	Vision inspection	I123474	Metrology Lab

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