Smart Virtual Product Development: Process Planning Module

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Abstract:

Smart Virtual Product Development (SVPD) system provides effective use of information, knowledge and experience in industry during the process of product development in Industry 4.0 scenario. This system comprises of three primary modules, each of which has been developed to cater to a need for digital knowledge capture for smart manufacturing in the areas of product design, production planning, and inspection planning. Manufacturing Capability Analysis and Process Planning (MCAPP) module is an important module of the SVPD system, and it involves the provision of manufacturing knowledge to experts working on product development at the early stages of the product lifecycle. In this research, we firstly describe the structure and working mechanism of the SVPD system's Manufacturing Capability Analysis and Process Planning (MCAPP) module. This is followed by validation of the MCAPP module's Manufacturing Process Planning (MPP) sub-module against the key performance indicators (KPIs) by using our threading tap case study. Our results verify the feasibility of our approach and show how manufacturing knowledge relating to features and functions can be used to enhance the manufacturing process across similar products during the early stages of product development. An analysis of the basic concepts and methods of implementation show that this is an expert system capable of supporting smart manufacturing which can play a vital role in the establishment of Industry 4.0.

Keywords: Smart virtual product development system (SVPD), Manufacturing Capability Analysis and Process Planning (MCAPP), Manufacturing Process Planning, Key Performance Indicators (KPIs), Industry 4.0.

1 Introduction and Background

Enormous amounts of information and knowledge are required at the design and manufacturing stages of the product development process in order to satisfy customer requirements. The process of product development does not rely solely upon the knowledge of new technological advancements but depends also upon a comprehensive understanding of the development of all related products past and present. Normally, this knowledge is held by different groups of experts working in a range of different areas which include product marketing, design, manufacturing, quality, and services. However, in practice, there are no clear boundaries that separate the stages of the product lifecycle, as they are all interconnected in some way. For example, a designer may need to work on such things as the selection of a suitable manufacturing process plan or matters of logistics in order to make cost-effective design decisions (Hayes et al., 2011).

Experts working on product development exploit knowledge from a wide range of areas. With respect to manufacturing, this knowledge relates to how the product can be manufactured to meet criteria such as cost, quality, and time to market. When considering the process of product development as a whole, the earlier that product developers are able to evaluate the manufacturability of their designs, the better (Hedberg Jr et al., 2017).

The integration of engineering design knowledge with manufacturing knowledge during early stages of the product development process is thus of great importance (Hong et al., 2004). The application of inappropriate manufacturing knowledge during product development can lead to mistakes, so it is important that designers can be confident that the knowledge they wish to apply is appropriate to the manufacturing facility they are working in. Designers often have to spend a lot of time searching for such knowledge, and this can result in delays to product development that can affect product quality and lead times. Evidence suggests that designers are often spending up to forty per cent of their work time searching for the right information, and this would obviously affect the productivity of a company investing in new product development processes (Rodgers and Clarkson, 1998).

Furthermore, the dawning of Industry 4.0 has brought with it the development of smarter and more complex products, major impacts to overall product lifecycles, and demands for changes to traditional product development processes (Nunes et al., 2017) . Effective decision-making at all stages of product development necessitates a comprehensive knowledge of each of the manufacturing processes involved and this includes a knowledge of all possible manufacturing outcomes. Engineering knowledge is embedded throughout the various stages of the product lifecycle in the form of rules, logical expressions, ontologies, predictive models, statistics, and information all acquired from previous experience and/or extracted from sensors used in areas such as production, inspection, product use, supplier networks, and maintenance. However, the ability to capture digital knowledge is limited and does not extend to all phases of the product life cycle, and this particularly applies to the manufacturing phase. With this in mind, organisations are therefore looking to streamline the capture and curation of digital knowledge across all phases of product development through the implementation of knowledge management strategies. These strategies require tools that are capable of analysing the kind of data and knowledge that is extracted from real time sensors and enterprise resource planning (ERP) systems used in production, product inspection, supplier networks, and maintenance. Such tools can be developed through the implementation of appropriate knowledge management techniques. (Feng et al., 2017).

The Manufacturing Capability Analysis and Process Planning (MCAPP) module of the SVPD system has been designed specifically with this in mind and is able to provide manufacturing knowledge to designers and product developers at the early stages of product development (Ahmed et al., 2020, Ahmed et al., 2019b, Ahmed et al., 2019c).

2 The Architecture of Smart Virtual Product Development (SVPD) System

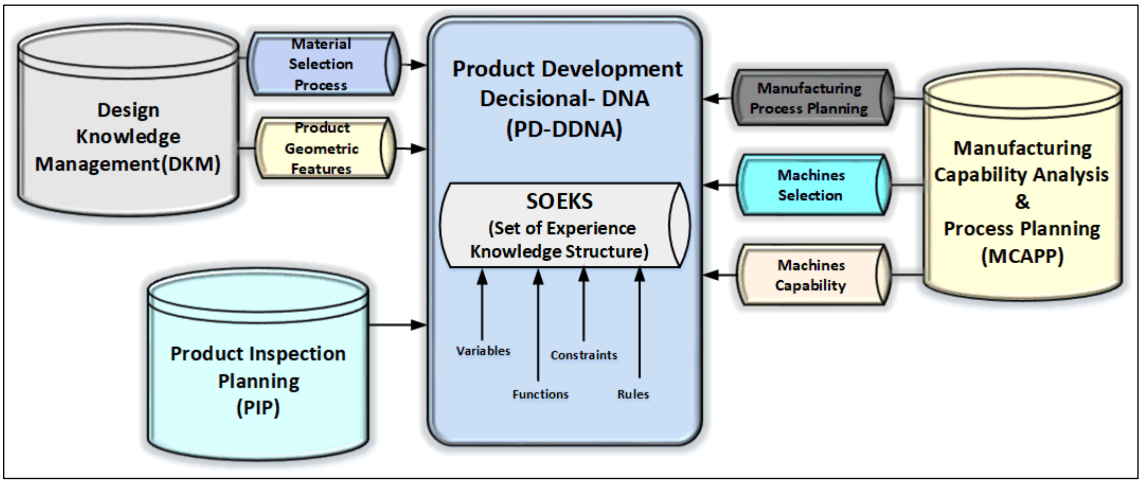

Figure 1: Architecture of SVPD system.

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 sets of experiences (SOEs) (Ahmed et al., 2020, Ahmed et al., 2019b, Ahmed et al., 2019c).

It is based on a smart knowledge management technique called set of experience knowledge structure (SOEKS or SOE) and decisional DNA, which were first presented by Sanin and Szczerbicki (Sanin and Szczerbicki, 2007, Sanin and Szczerbicki, 2009). The main components of SOE are variables, functions, constraints, and rules. Variables are the source of other SOE components and are the centre root or the starting point of the structure. Functions create relationships between variables and are used to develop multi-objective goals. Constraints are also functions and they are applied by SOE to get feasible solutions and to control system’s performance with respect to defined goals. Rules, on the other hand, are the conditional relationships among the variables and are defined in terms of IF-THEN-ELSE logical statements. Therefore, a formal decision event is represented by a unique set of variables, functions, constraints, and rules within the SOE.

The SVPD system has been developed to address a need for digital knowledge capture in the areas of product design, production planning, and inspection planning in smart manufacturing (Feng et al., 2017) 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 1. The system will allow the development of new products from existing products or families of products, using hierarchies and virtual tools as described earlier in this chapter. 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. These modules interact with the system's DDNA knowledge repository, in which is held experiential knowledge acquired from previous projects. This knowledge is stored as SOEs in the form of either VEOs or VEPs.

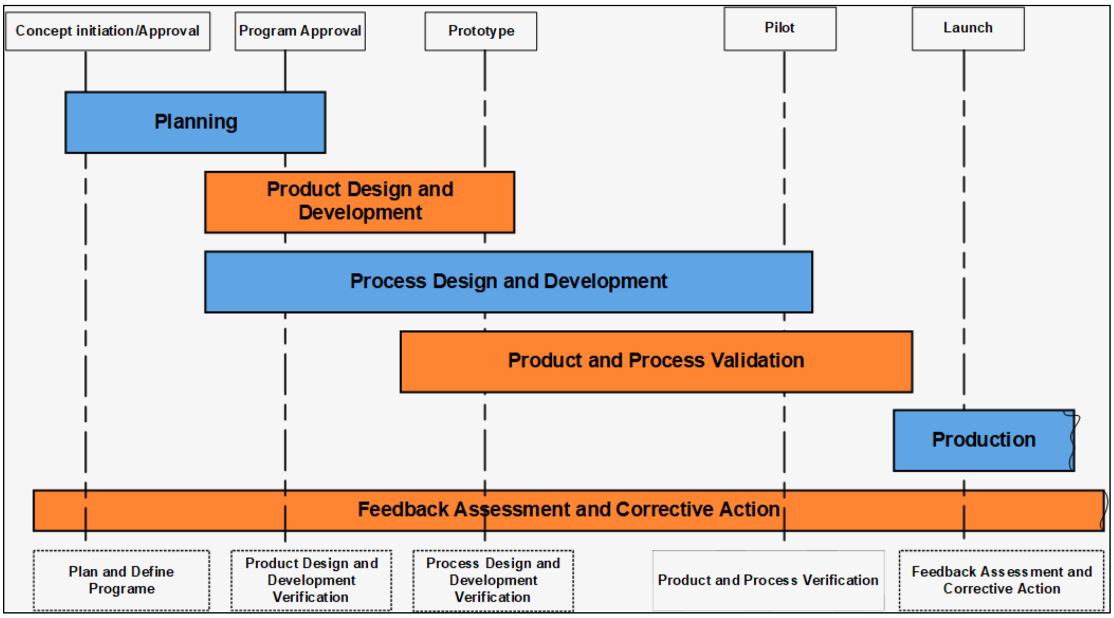

Figure 2: The various phases of APQP methodology.

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 2 (Stamatis, 2001, Stamatis, 2018).

3 Developing and Testing of the MCAPP Module

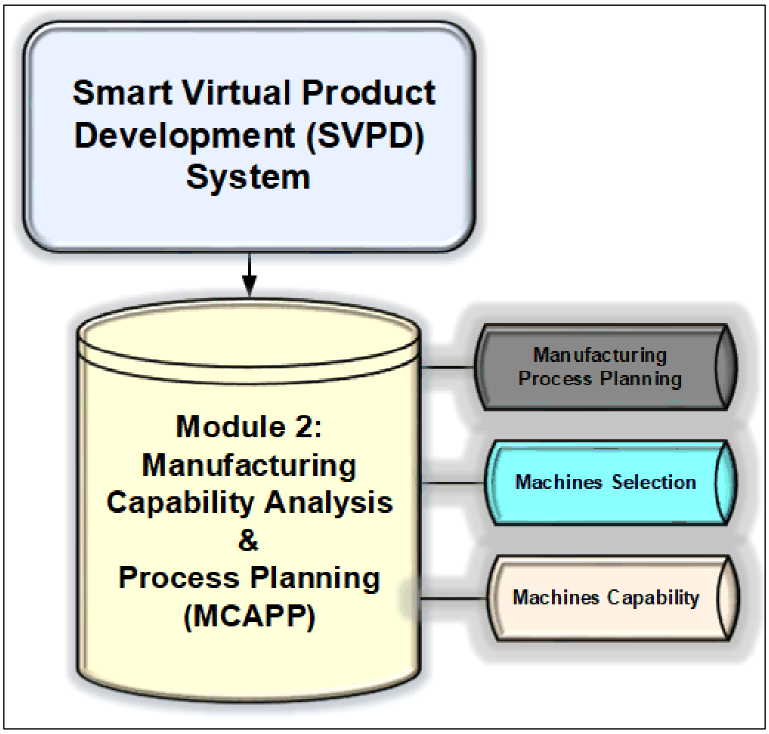

Figure 3: Structure of the MCAPP module.

The MCAPP module is the second module of the SVPD system. It deals with important aspects of the manufacturing capability analysis and process planning stages of product development (Ahmed et al., 2020, Ahmed et al., 2019b, Ahmed et al., 2019c). As shown in Figure 3, this module comprises of three sub-modules, these being the Manufacturing Process Planning (MPP) sub-module, the Machine Selection (MS) sub-module, and the Machine Capability (MC) sub-module. We introduced a case study involving the design and development of a threading tap which was conducted in order to validate all modules of the SVPD system (Ahmed et al., 2020, Ahmed et al., 2021, Ahmed et al., 2018). Initially the DKM module was used to select the appropriate material and to create geometric features for the threading tap. The variables and functions pertaining to these are then used as input for the MCAPP sub-modules (Bilal Ahmed et al., 2019, Ahmed et al., 2019a, Ahmed et al., 2020).

3.1 Working Algorithm of MCAPP Module

- *Reads Variables, Functions, Constraints, and Rules.*
- *Develops Set of Variables, Set of Functions, Set of Constraints, and Set of Rules.*
- *Creates a Set of Experience (SOE) = Set of Variables + Set of Functions +Set of Rules.*
- *Form a chromosome of manufacturing process planning by collecting SOEs of the same category.*
- *Provides top 5 proposed solutions.*
- *User selects the final solution and it is saved as SOE in DDNA of SVPD system for the future reference.*

Figure 4: Pseudocode for parser reading CSV file for MCAPP sub-modules.

The working algorithms of the three sub-modules of MCAPP are similar to each other. In each one, important variables and functions involved in manufacturing process planning are stored as SOEKS in a comma-separated values (CSV) file, and weighting is assigned to the characteristics of each variable.

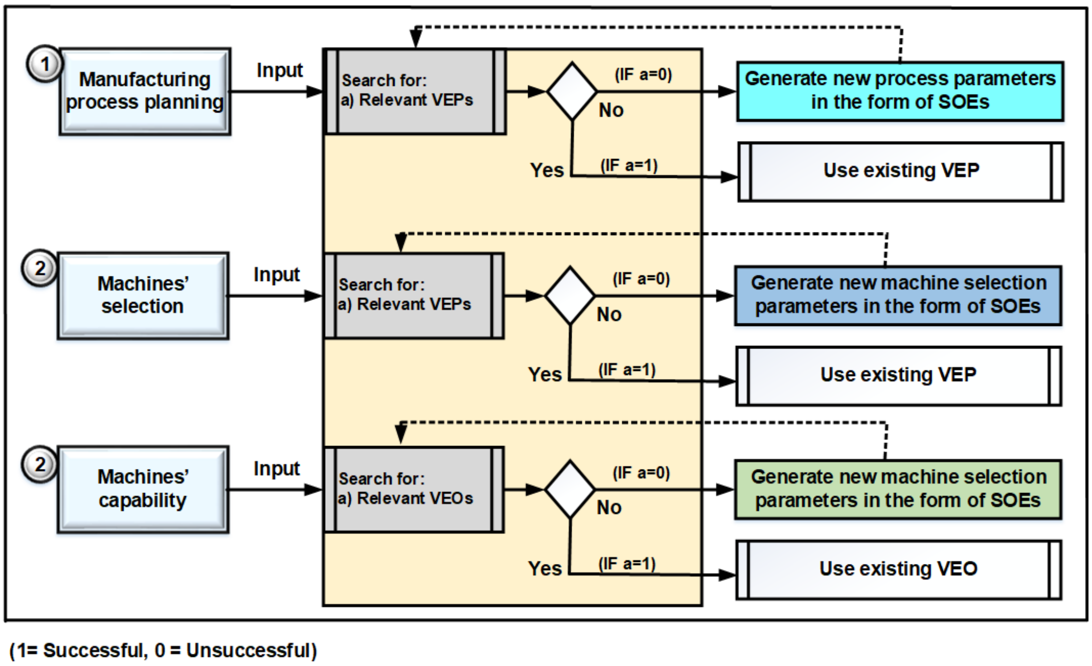

Figure 5: Working Algorithm of MCAPP module.

A similar procedure is followed for the storage of both machine selection data and machine capability data, with the only difference being that the machine selection process SOEKS are saved as a VEP, while the machine capability SOEKS are saved as a VEO. The CSV file component of manufacturing process planning is shown in

Appendix 1 for illustrative purposes. After the data has been stored, the next step is then to write the parsers capable of reading each these CSV files. As JAVA was used in the construction of the SOEKS and DDNA, it was chosen also when writing the parsers. The three parsers are as follows:

a. mppParserCSV
b. msParserCSV
c. mcParserCSV

The pseudocode for each of these parsers is given in Figure 4, whereas Figure 5 shows the generic working mechanism of each of the sub-modules of the MCAPP module. The same parsing procedure applies to each of these sub-modules (Ahmed et al., 2019b).

3.2 Graphical User Interface (GUI) for the MCAPP Module

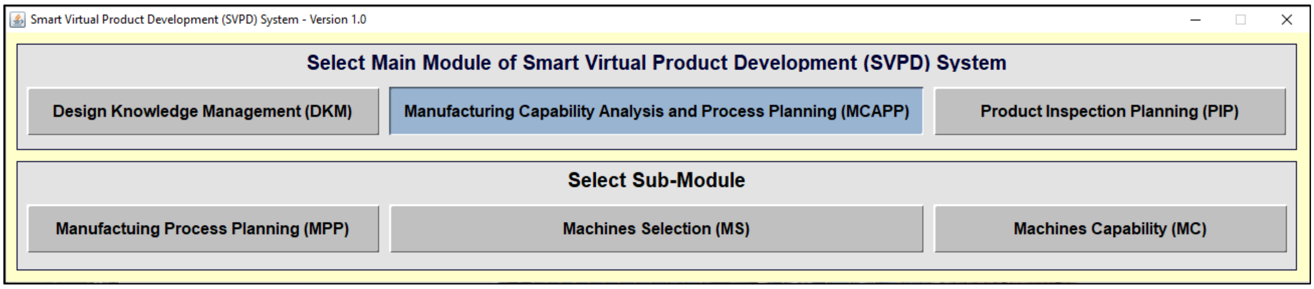

Figure 6: Structure of the MCAPP module.

The GUI for the SVPD system is shown in Figure 6. After logging in, the user is prompted to make a selection from among the system's three main modules. If the MCAPP module is selected, the user is then prompted to select one or other of the three MCAPP sub-modules. Subsequently, if the MPP sub-module is selected, the user then 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 material for the product is selected from the 'Select material' dropdown (see Figure 7). This dropdown provides a list of materials. The user chooses the material, enters the relevant code into the text box below, and then clicks the 'Add material' button. The selection of critical variables then proceeds in a similar way, whereby the user selects the value related to a required critical variable from a dropdown, enters that 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 and critical variables selections have been made, they appear below in the ‘Built query’ section of the screen (see Figure 4.9) and a possible random query structure is shown below:

- *Product Name = Threading Tap*
- *High Speed Steel = T11301*
- *Hardness = 60*
- *Density = 7*
- *Type of use = Machine use*

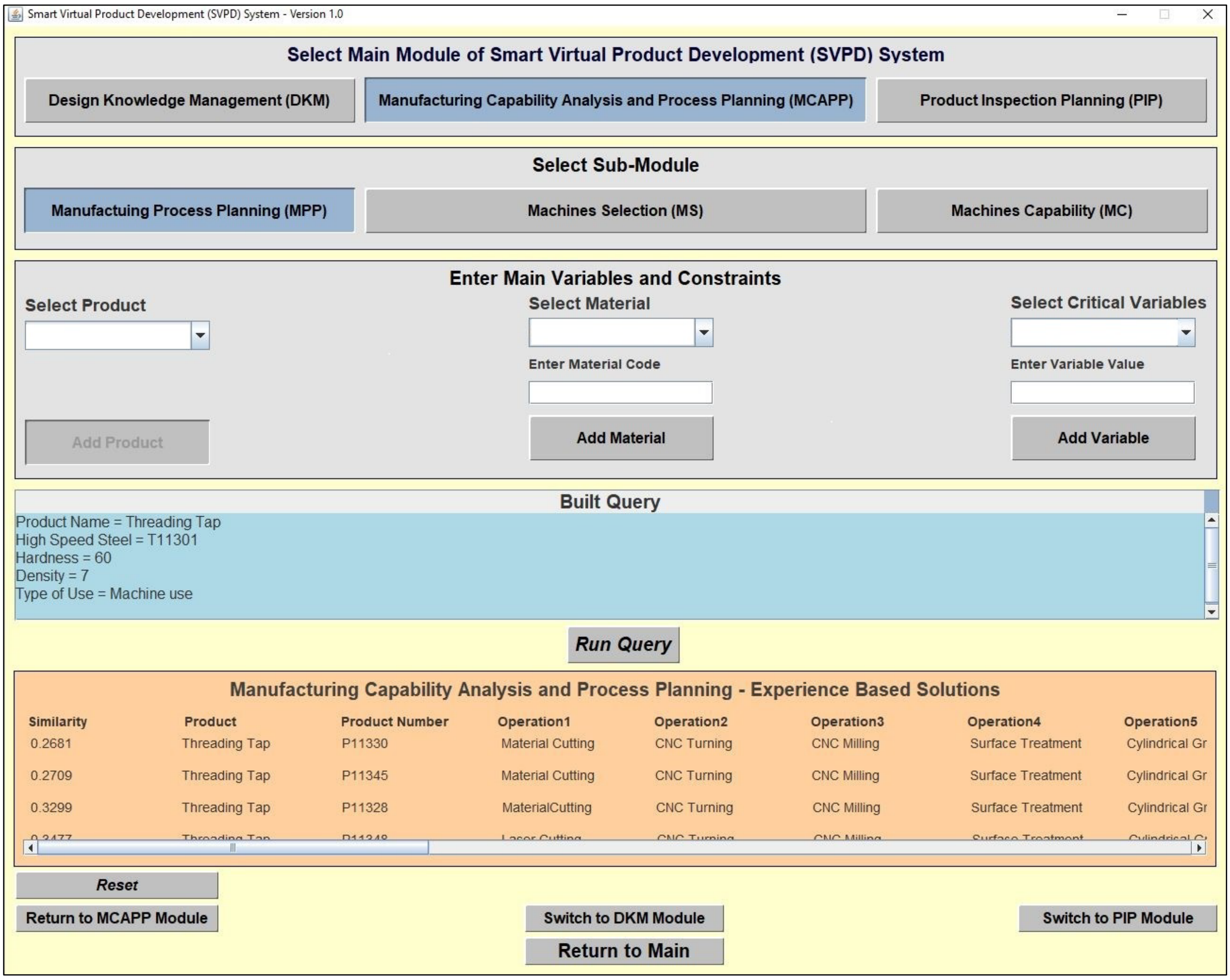

Figure 7: GUI for building queries for the MPP sub-module.

Finally, after the user clicks the ‘Run Query’ button, SOEs that most closely match the query are retrieved, and appear below in the ‘Manufacturing Capability Analysis and

Process Planning – Experience Based Solutions' section of the screen. These SOEs contain output including the similarity of the query SOE to the output SOE, the product name, the relevant material, and all the manufacturing operations required to manufacture the selected product. The screens for the other two sub-modules of the MCAAP module work in the same way (Ahmed et al., 2020).

4 Results and Discussion

The case study for MCAPP module was executed on a Dell laptop with Windows 10 Enterprise 64-bit operating system having Intel ® Core ™ I5-7300u CPU @ 2.60 and 8 GB of RAM. The following provides a general analysis of a case study undertaken to check the robustness of the system.

4.1 Parsing time for CSV file and SOEKS elements of the MCAPP module

The parsing times for the various SOEKS elements for the MPP, MS and MC sub-modules are shown in Figure 8. The parser for the MPP sub-module reads data from a CSV file that holds information relating to around 20 different types of tool including threading tools, drills, reamers and milling cutters. This file stores information about manufacturing processes as SOEs, and comprises 200 variables, 20 functions, and 3 constraints overall (Ahmed et al., 2020). The parsing processes for each of the MCAPP, MS and MC decisional chromosomes were executed, with parsing times of 0.098 seconds for mppParserCSV, 0.093 for msParserCSV and mcParserCSV 0.072 being recorded (see Figure 8), which – when taking into the account the size and complexity of the SOEKS – is an excellent result.

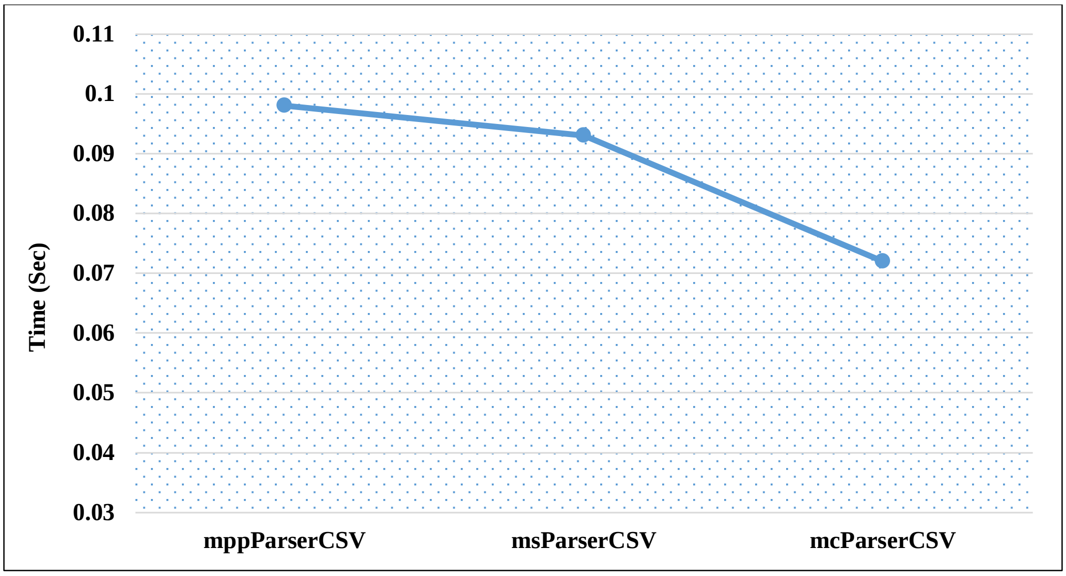

Figure 8: Time taken to parse the MPP, MS and MC submodules.

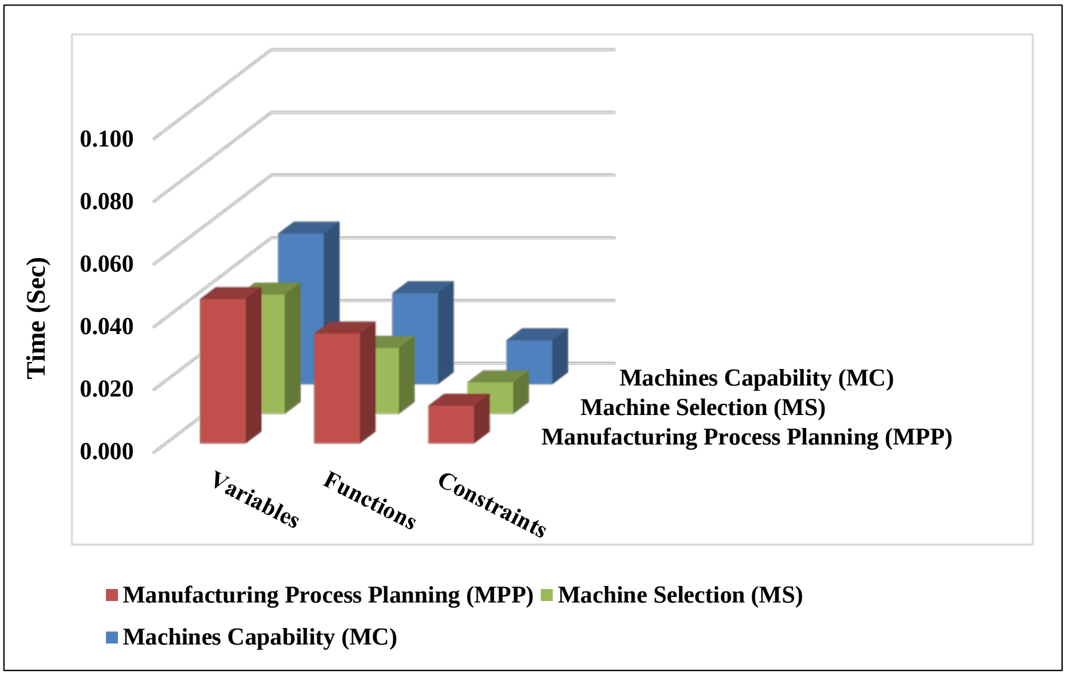

Figure 9: SOEKS elements vs parsing time for the MCAPP sub-modules.

The parsing times for the different SOE elements of the MPP sub-module were 0.035 seconds to read variables, 0.046 seconds to read functions, and 0.012 seconds to read constraints. Figure 7 compares the parsing times for the SOE elements of the MPP, MS and MC sub-modules. Pareto analyses of the parsing times for each of these three sub-modules is shown in Figures 10, Figure 11, and Figure 12. From these figures we can see that in the case of all three sub-modules, variables are the most time-consuming elements to parse.

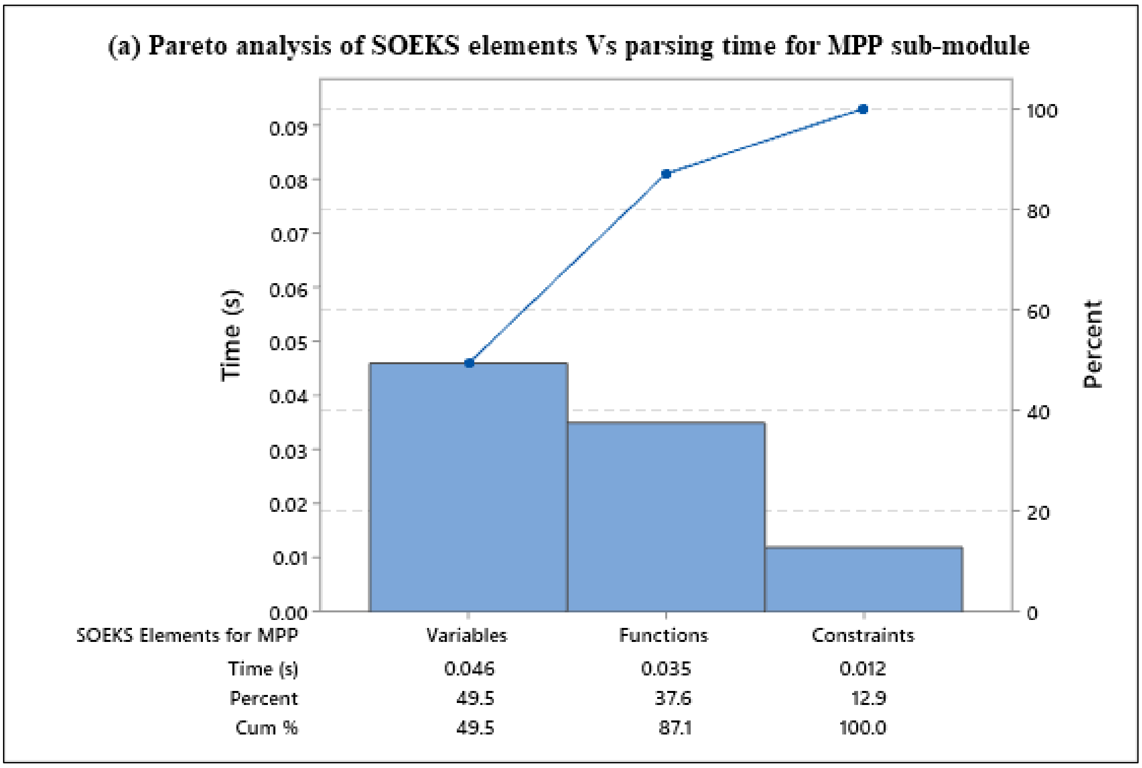

Figure 10: Pareto analysis of SOEKS elements vs parsing times for the MPP sub-module.

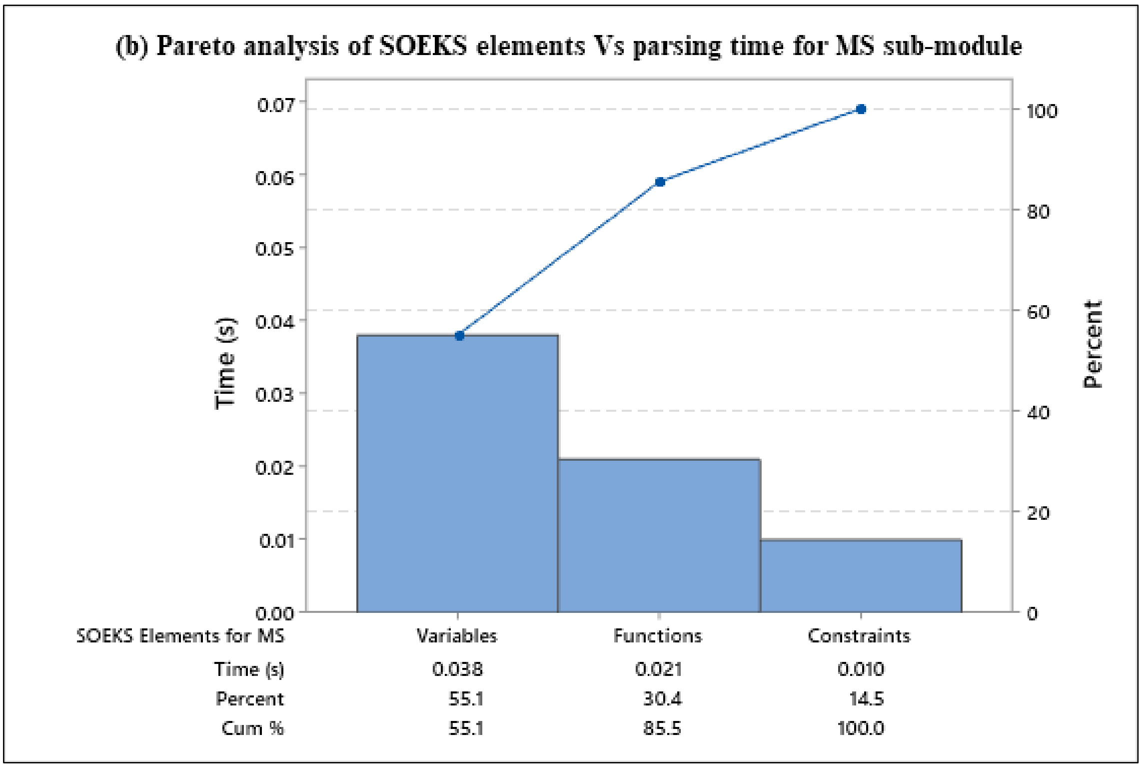

Figure 11: Pareto analysis of SOEKS elements vs parsing times for the MS sub-module.

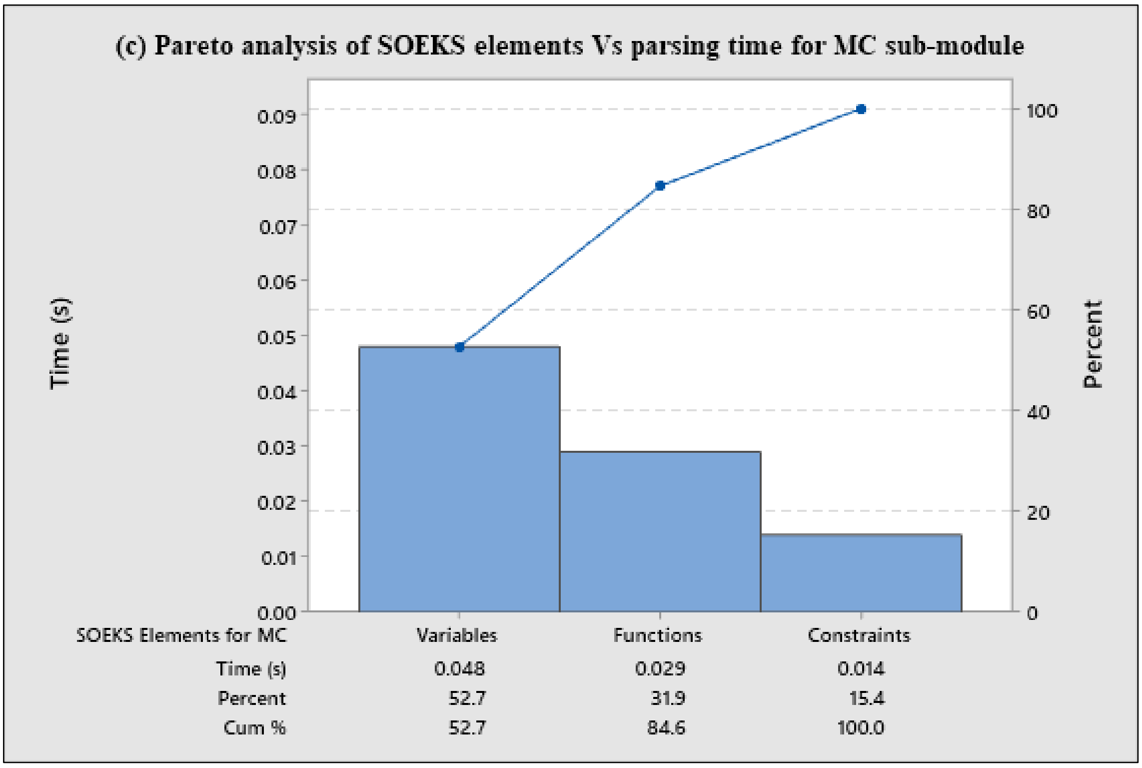

Figure 12: Pareto analysis of SOEKS elements vs parsing times for the MC sub-module.

4.2 Searching for the most similar SOEs

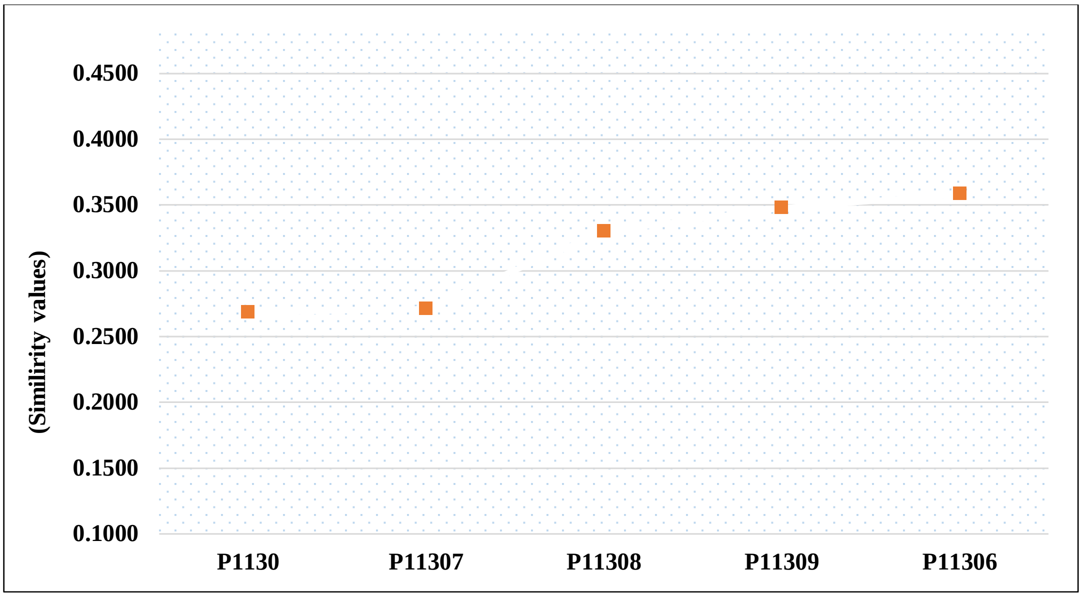

Figure 13: Similarity values for the SOEKS of five stored products.

The MCAPP module's graphical user interface (GUI) is used to find SOEKS that are most similar to queries relating to each of the MCAPP sub-modules. This interface is an extension of the DKM module's GUI. After the user uses the GUI to input a query based on some initial objectives the similarity values of 10 tools stored as SOEs in terms of variables, functions and constraints are then retrieved from the system. An example of these similarity values is shown in Figure 13 (Ahmed et al., 2020).

The similarity between the query and each of the SOEs is calculated on the basis of Euclidian distance, and can take a value from 0 to 1, where a value of zero equates to the greatest similarity. Given a pair of SOEs made up of a SOE $mppDNA_i$ (the entire MCAPP-DNA repository) and the query SOE_j (a SOE made up of the query) ∈ S, it is possible to generate a similarity metric for the variables called SV ∈ [0,1] by calculating the distance between each of the pairwise attributes k ∈ $mppDNA_i$ and $QuerySOE_j$. The Euclidean distance measurement has been selected on account of its simplicity and how extensively it is used. In keeping with the notion of a range of comparison, the 'maximum function' normalisation form was also included. The similarity metric is expressed as per the following equation:

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

where $mppDNA_{ik}$ and $QuerySOE_{jk}$ are the k^{th} attribute of the sets $mppDNA_i$ and $QuerySOE_j$, w_k is the weight given to the k^{th} attribute (in this case the variable) and n is the number of variables in $mppDNA_i$.

The similarity metric for machine selection and machine capability will then take the following forms:

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

$$S_v(mcDNA_i, QuerySOE_j) = \sum_{k=1}^{n} w_k \left[\frac{|mcDNA_{ik}^2 - QuerySOE_{jk}^2|}{\max(|mcDNA_{ik}|, |QuerySOE_{jk}|)^2}\right]^{0.5} \forall k \in \boldsymbol{mcDNA_i} \wedge \boldsymbol{QuerySOE_j} \quad (3)$$

3 Conclusion

In this research, we presented the concept of enhancing the product development process by providing manufacturing knowledge during early stages of product development process. We were able to achieve this enhancement using our SVPD system's MCAAP 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 manufacturing process by using the previously acquired experiential knowledge of similar products.

The MCAPP module of the system can be used to generate manufacturing process plans, to select suitable machines for the selected processes, and to determine the capability of selected machines. 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 process 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 Systems Applications and Products (SAP) or oracle discrete manufacturing would lead to more enhanced decision-making in relation to product manufacturing processes. In the next chapter, the last module of the SVPD system is introduced, described, and then validated in the case study involving production of a threading tap.

Appendix 1: CSV file component for the MPP sub-module.

Variables									
Product_Name	Product_Number	Material_UNS_Code	Material_Hardness	Material_Density	Operation_01	Operation_02	Operation_03	Operation_04	Operation_05
Threading Tap	P11330	T11302	62	8.16	Material Cutting	CNC Turning	CNC Milling	Surface Treatment	Cylindrical Grinding
Threading Tap	P11329	T11323	66	8.16	Material Cutting	CNC Turning	CNC Milling	Surface Treatment	Cylindrical Grinding
Threading Tap	P11342	T11304	65	7.97	Material Cutting	CNC Turning	CNC Milling	Surface Treatment	Cylindrical Grinding
Threading Tap	P11347	T11307	65	7.95	Material Cutting	CNC Turning	CNC Milling	Surface Treatment	Cylindrical Grinding
Reamer	P12101	T12001	65	8.67	Material Cutting	Turning	CNC Milling	Surface Treatment	Cylindrical Grinding
Threading Tap	P11345	T12002	62	7.86	Material Cutting	CNC Turning	CNC Milling	Surface Treatment	Cylindrical Grinding
Drill	P13108	T12004	66	8.68	Material Cutting	Turning	Milling	Surface Treatment	Cylindrical Grinding
Threading Tap	P11350	T12005	66	8.75	Material Cutting	CNC Turning	CNC Milling	Surface Treatment	Cylindrical Grinding
Milling Cutter	P15111	T12015	46	8.19	Material Cutting	Turning	CNC Milling	Surface Treatment	Cylindrical Grinding
Threading Tap	P11356	T12015	46	8.19	Material Cutting	CNC Turning	CNC Milling	Surface Treatment	Cylindrical Grinding

References

AHMED, M. B., MAJEED, F., SANIN, C. & SZCZERBICKI, E. 2020. Enhancing Product Manufacturing through Smart Virtual Product Development (SVPD) for Industry 4.0. *Cybernetics and Systems*, 51**,** 246-257.

AHMED, M. B., MAJEED, F., SANIN, C. & SZCZERBICKI, E. 2021. Experience-Based Product Inspection Planning for Industry 4.0. *Cybernetics and Systems***,** 1-13.

AHMED, M. B., SANIN, C., SHAFIQ, S. I. & SZCZERBICKI, E. 2019a. Experience based decisional DNA to support smart product design. *Journal of Intelligent & Fuzzy Systems***,** 1-9.

AHMED, M. B., SANIN, C. & SZCZERBICKI, E. 2018. Experience-Based Decisional DNA (DDNA) to Support Product Development. *Cybernetics and Systems***,** 1-13.

AHMED, M. B., SANIN, C. & SZCZERBICKI, E. Implementing Smart Virtual Product Development (SVPD) to Support Product Manufacturing. Asian Conference on Intelligent Information and Database Systems, 2019b. Springer, 464-475.

AHMED, M. B., SANIN, C. & SZCZERBICKI, E. 2019c. Smart Virtual Product Development (SVPD) to Enhance Product Manufacturing in Industry 4.0. *Procedia Computer Science*, 159**,** 2232-2239.

BILAL AHMED, M., IMRAN SHAFIQ, S., SANIN, C. & SZCZERBICKI, E. 2019. Towards experience-based smart product design for industry 4.0. *Cybernetics and Systems*, 50**,** 165-175.

FENG, S. C., BERNSTEIN, W. Z., HEDBERG, T. & FEENEY, A. B. 2017. Toward Knowledge Management for Smart Manufacturing. *Journal of computing and information science in engineering*, 17**,** 031016.

HAYES, C. C., GOEL, A. K., TUMER, I. Y., AGOGINO, A. M. & REGLI, W. C. 2011. Intelligent support for product design: Looking backward, looking forward. *Journal of Computing and Information Science in Engineering*, 11**,** 021007.

HEDBERG JR, T. D., HARTMAN, N. W., ROSCHE, P. & FISCHER, K. 2017. Identified research directions for using manufacturing knowledge earlier in the product life cycle. *International journal of production research*, 55**,** 819-827.

HONG, P., DOLL, W. J., NAHM, A. Y. & LI, X. 2004. Knowledge sharing in integrated product development. *European journal of innovation management,* 7**,** 102-112.

NUNES, M. L., PEREIRA, A. & ALVES, A. 2017. Smart products development approaches for Industry 4.0. *Procedia Manufacturing,* 13**,** 1215-1222.

RODGERS, P. A. & CLARKSON, P. J. 1998. Knowledge usage in new product development (NPD).

SANIN, C. & SZCZERBICKI, E. 2007. Towards the construction of decisional DNA: A set of experience knowledge structure java class within an ontology system. *Cybernetics and Systems: An International Journal,* 38**,** 859-878.

SANIN, C. & SZCZERBICKI, E. 2009. Experience-based knowledge representation: SOEKS. *Cybernetics and Systems: an international journal,* 40**,** 99-122.

STAMATIS, D. H. 2001. *Advanced quality planning: A commonsense guide to AQP and APQP*, Productivity Press.

STAMATIS, D. H. 2018. *Advanced product quality planning: the road to success*, CRC Press.