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KNOWLEDGE BASED MODELLING FRAMEWORK FOR FLEXIBLE MANUFACTURING SYSTEM

Syed Imran Shafiq[(a)], Cesar Sanin[(b)] , Edward Szczerbicki[(c)],

[(a)]Faculty of Engineering and Technology, Aligarh Muslim University, Aligarh, India
[(b)] Faculty of Engineering and Built Environment, The University of Newcastle, Callaghan, NSW, Australia, [(c)]Faculty of Management and Economics, Gdansk University of Technology, Gdansk, Poland

[(a)] Sishafiq.bp@amu.ac.in, [(b)] Cesar.Sanin@newcastle.edu.au, [(c)]Edward.szczerbicki@zie.pg.gda.pl

ABSTRACT

This paper proposes knowledge-based modelling framework to manage the storage, analysis, and processing of data, information, and knowledge of a typical Flexible Manufacturing System (FMS). The framework utilizes the concept of virtual engineering object (VEO) and virtual engineering process (VEP) for developing knowledge models of FMS to achieve effective scheduling and manufacturing flexibility. The proposed generic model is capable of capturing in real time the manufacturing data, information and knowledge at every stage of production i.e. at the object level, the process level, and at the factory level. The significance of this study is that it supports decision making by reusing past decisional experience, which will not only help in effective real time data monitoring and processing but also make FMS system more intelligent and ready to function in the virtual Industry 4.0 environment.

Keywords: knowledge representation, knowledge based model, computer integrated manufacturing

1. INTRODUCTION AND BACKGROUND

A flexible manufacturing system (FMS) is a method for producing goods that is readily adaptable to changes in the product being manufactured, both in type and quantity. Machines and computerized systems are configured to manufacture different parts and handle varying levels of production. A flexible manufacturing system (FMS) gives manufacturing firms an advantage to quickly change a manufacturing environment to improve process efficiency and thus lower production cost. FMS is defined as an integrated, computer-controlled complex system of automated material handling devices and numerically controlled tools that can simultaneously process medium-size volumes of medium variety parts (Yadav and Jayswal 2018). Two basic manufacturing flexibility types are proposed: machine flexibility and routing flexibility. Based on these basic flexibility types other types of flexibility like product flexibility, process flexibility, operation flexibility, volume flexibility, expansion flexibility and production flexibility can be derived.

Due to advantages associated with FMS, it is an area of interest from earlier days (Groover 2007). Researchers were working on improving the performance of FMS with application of various techniques. Earlier analytical methods were used for accessing FMS performance (Stecke 1986) but with growing technology, simulation, artificial intelligence, Petri Nets etc. modelling techniques have gained importance too (Yadav and Jayswal 2018).

Investigation of work that are accomplished by using different modelling techniques in FMS like mathematical, artificial intelligence, hierarchical, multi criteria decision-making method, Petri Nets and simulation have some drawbacks as well some advantages. The drawbacks associated with mathematical modelling are the stated assumptions, as they may not be valid in real world. Also the process of computation becomes large with increase in the size of the problem. For analyzing different system performance measures of FMS and seeing how they behave with constraints in particular conditions, the process of modelling and simulation is the best one. For avoiding and protecting the occurrence of deadlock in the FMS system, Petri Net models are used generally. Selection of various machine and parts in FMS can be done effectively by using mathematical and MCDM techniques. FMS control can be done efficiently by using artificial intelligence technique. Selection of best dispatching rule from given alternatives is well evaluated by MCDM and artificial intelligence techniques (Yadav and Jayswal 2018). Thus, general purpose modelling technique for implementation, design and control of FMS is needed.

This paper proposes a multipurpose framework, in which previous knowledge of the FMS along with information communication technology (ICT) features are utilized to induce intelligence to the FMS system. The proposed model enables micro level integration of various FMS components and processes, which in turn will not only facilitate the real-time control and monitoring capabilities but also enhance effective decision making.

2. KNOWLEDGE BASED FMS MODEL

The hypothetical framework for the proposed FSM model is presented in Figure 1. It represents a typical FMS configuration assumed for modelling and research purposes (Ali and Wadhwa 2010).

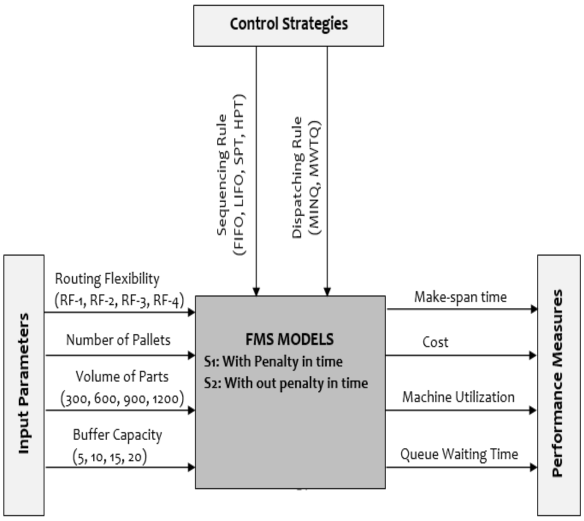

Figure 1: Framework for proposed FMS model

The above FMS framework was modeled using unique knowledge representation technique called Decisional DNA together with the concepts of Virtual Engineering Object and Virtual Engineering Process which are presented next.

2.1. Set of Experience and Decisional DNA

One of the challenges of the Semantic Web society is smart storage of information and knowledge in artificial systems, so it can be unified, enhanced, reused, shared, communicated and distributed between artificial systems (Shabolt et al. 2006). Our DDNA concept introduces one of the key components of addressing the above challenge. This concept stems from the role of deoxyribonucleic acid (DNA) in storing and sharing information and knowledge. The idea behind our approach was to develop an artificial system, an architecture that would support discovering, adding, storing, improving, and sharing information and knowledge among machines, processes and organisations through experience. We proposed a novel Knowledge Representation (KR) approach in which experiential knowledge is represented by Set of Experience (SOE; Figure 2) and is carried into the future by Decisional DNA (DDNA; Figure 3) (Sanin and Szczerbicki 2004, Sanin et al 2009).

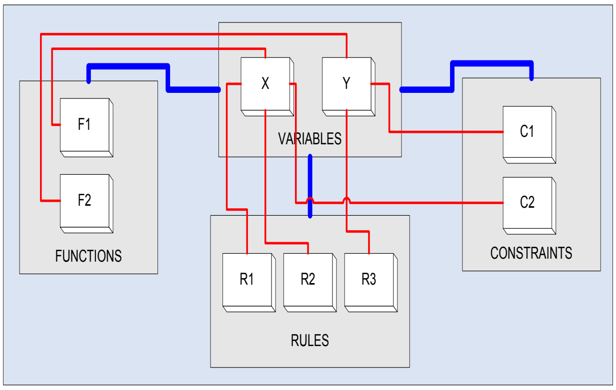

Figure 2: Structure of SOE

As illustrated in Figure 2, SOE is the combination of 4 components that characterise decision making actions (variables V, functions F, constraints C, and rules R) and it comprises a series of mathematical concepts (logical element), together with a set of rules (ruled based element), and it is built upon a specific event of decision-making (frame element).

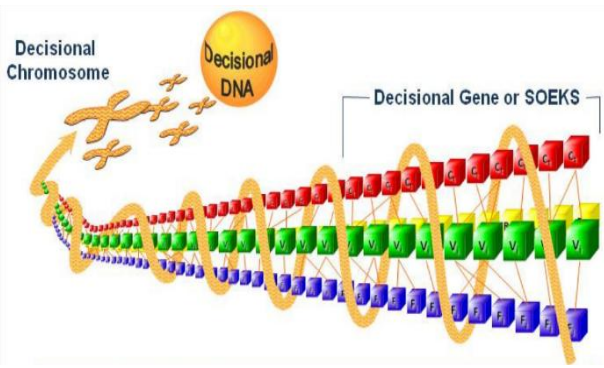

Figure 3: Sets of Experience (Decisional Genes) are grouped according to their phenotype, creating Decisional Chromosomes, and groups of chromosomes create the Decisional DNA

SOE and DDNA can be implemented on various platforms (e.g. ontology, reflexive ontology, software based, fuzzy logic etc.) in multi domains, which makes it a universal approach. We initially developed the concept and coined the expressions of SOE and DDNA in Sanin, Szczerbicki 2008, and Zhang et al 2016. Since then our research efforts resulted in widespread recognition of this innovative KR technique based on DNA metaphor that is presented as multi-technology shareable knowledge structure for decisional experience with proven security and trust in Sanchez et al 2014, Sanin et al 2012a, Shafiq et al 2014a, Sanin et al 2012b, Wang et al 2015. Subsequently, DDNA was used to develop Virtual Engineering Object (VEO) and Virtual Engineering Process (VEP) as presented next.

3. VIRTUAL ENGINEERING OBJECT (VEO)

VEO is developed on the concept of cradle-to-grave approach, which means that the contextual information and decision-making regarding an engineering object right for its inception until its useful life is stored or linked in it. The knowledge representation technique of Set of experience knowledge structure (SOEKS) and Decisional DNA (DDNA) ((Sanin Szczerbicki 2005, 2006, 2009, Sanin et al 2007, Zhang et al 2010) is used for developing this model. SOEKS-DDNA provides dynamicity to VEO to overcome issues related to representation of complex and discrete objects (Shafiq et al 2014b).

VEO of an engineering object implies that knowledge and experience related with that object is stored in a structured manner in a repository. This information not only can be used for decision-making regarding its better operational performance but also can be utilized in areas like maintainability, serviceability and reliability of the object. The concept VEO involves the interlinking of the body of knowledge of connected objects, with the aim of constructing subclasses consistent enough for the purposes of the classification scheme.

A VEO can encapsulate knowledge and experience of every important feature related with an engineering object. This can be achieved by gathering information from six different aspects of an object: *Characteristics, Functionality, Requirements, Connections, Present State,* and *Experience,* as illustrated in Figure 4.

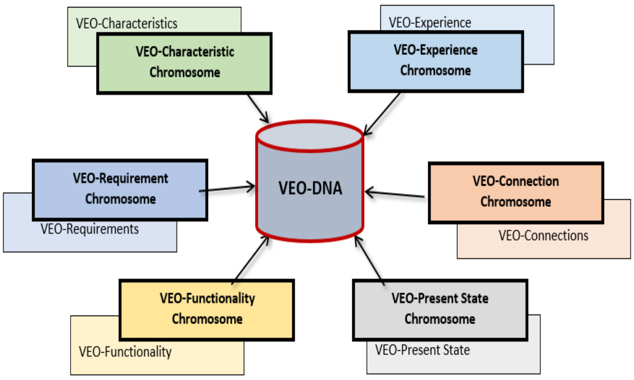

Figure 4: Architecture of a VEO

In each VEO model, the collection of SOEKS combines to form VEO-DNA (see Fiure. 4) Thus, a VEO is knowledge representation of an engineering artefact, and it has three vital features (Shafiq et al 2015a, 2015b)

- the embedding of the decisional model expressed by the set of experience,
- a geometric representation and
- the necessary means to relate such virtualization with the physical object being represented.

4. VIRTUAL ENGINEERING PROCESS (VEP)

The next step in our modelling process is the extension of VEO concept to engineering process or process planning. Dynamic manufacturing environments require a flexible process planning and control system in response to changing manufacturing resource availability, production uncertainty and dynamic machining conditions.

Process planning involves selection of necessary manufacturing processes. It includes determination of manufacturing sequences and the selection of resources needed to 'transform' a design model into a physical component. Therefore, a general, adaptive, resource efficient and experience-based framework with VEP modules comprising VEO is developed. VEP is designed for knowledge representation and decision-making at the shop floor level.

The VEP information model encompasses multiple perspectives of different machining stages and scales, from process planning, machining, to machining feedback which is presented in the next Section.

4.1. Architecture of VEP

Process planning is combination of information regarding the operation required, manufacturing sequence, and machines required. In addition to this, for VEP, information of all the VEOs of the resource associated with the process is also required. Therefore, to encapsulate knowledge of the above-mentioned areas, the VEP is designed having following three main elements or modules (see Figure 5):

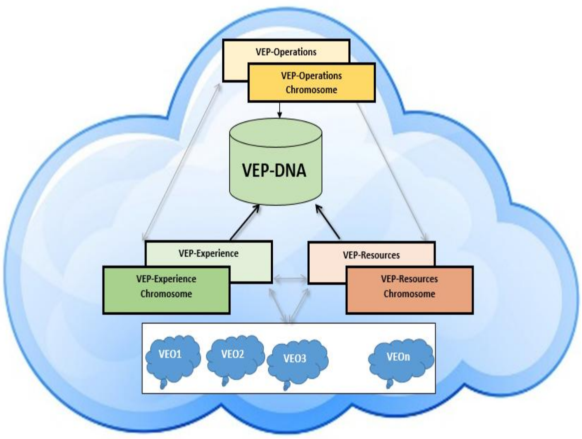

Figure 5: Configuration of a VEP and network with VEOs

(i) Operations - In this module of VEP, all the information related with the operations that are required to manufacture an engineering object is stored. This includes knowledge in the form of SOEKS related to operation process and scheduling. Furthermore, functional dependencies between operations are also part of operations. These are sub categorized 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, urgency.

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

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

Furthermore, the information of VEO categorized under *Characteristics, Requirements, Functionality, Present state, Connections, Experience* is also linked in this section

(iii) Experience - In the experience section, links to the SOEKS of VEOs along with VEP having past formal decisions to manufacture engineering components are stored. They represent the links to SOEKS based on past experience on that particular machine to perform given operation along with operational and routing parameter.

As demonstrated in Figure 5, VEP is also envisaged on cloud computing platform to facilitate delivery of compressed information on complex interrelationships within the modelled process.

5. FMS MODELLING FRAMEWORK AND ITS IMPLEMENTATION

The Decisional DNA based FMS is designed and developed to enable the FMS to capture formal decisional events and to capture, extract, reuse, and share knowledge.

As discussed in section 4, that VEO is a knowledge representation of engineering artefacts. In this study each physical component of FMS is considered as a VEO and correspondingly knowledge models are developed for every machine and job i.e. M1-VEO, M2-VEO, M3-VEO, M4-VEO, M5-VEO, M6-VEO, JI-VEO, J2-VEO etc. Each VEO knowledge model having information regarding its *characteristic*, *functionality*, *requirement*, *connections*, *present-state* and *experience* (see Figure 5.) of the physical object. Furthermore, adhering to the structure of SOEKS-DDNA, for each module, information is structured according to variables, function, constant and rules related with every formal decision. On the same pattern information of characteristics, requirement, connections, present state, functionality related to M1-VEO are gathered. CSV files storing SOEKS were generated through arena simulation software for M1-VEO, M2-VEO, M3-VEO, M4-VEO, M5-VEO, M6-VEO, JI-VEO.

Moreover, the routing flexibility is treated as a process and a DDNA based VEP model is developed. SOEKS for VEP elements: *operations*, *resources* and *experience* were also stored in CSV file. For each VEP elements i.e. *operations*, *resources* and *experience*; SOEKS variables, functions constraint and rules are defined. Having these files, a parser is written in Java programming language to read SOEKS stored in the CSV format. Parser looks for CSV file, in that file it looks for the word ‘variables’, then starts reading the first row under variables. Once all the variables of the first row are read then the parser looks for the word ‘functions’, it reads all the rows under functions.

After that it looks for word ‘constraints’ and read all the rows under constraints. This entire information i.e. first row under ‘variables’, all rows under ‘functions’ and ‘constraints’ are stored as one set of experience (SOEKS or SOE).

This cycle is repeated for all rows under ‘variables’, for each row along with functions and constraints, SOEKS are created.

Same procedure is repeated for the all the other CSV files. Each file representing a category, collection of SOEKS of same category forms a chromosome of either of VEO or VEP. Collection of all chromosomes forms a Decisional DNA of a FMS i.e. FMS-DNA as shown in Figure 6. Once the VEO chromosome is constructed, decisional DNA has feature that it can be queried.

Once all the relevant experience of FMS-VEP and associated VEO’s is captured, entire process planning and control of FMS can be virtually represented.

Moreover, this experience can be utilized for future performance evaluation of similar FMS scenario. This approach will not only be beneficial for better resource utilization but also in cost-effective quality production.

Figure 6 shows the proposal for the case study. First, VEOs of machines/resources (M1-VEO, M2-VEO, M3-VEO, M4-VEO, M5-VEO, M6-VEO, J1-VEO etc.) required for the functioning of FMS developed. Then the VEP to decide the routing flexibility is developed based on the case-specific experience of that manufacturing system. VEOs along with experience of engineering process (VEP) form an FMS experience repository. JAVA programming language is used to develop and implement this concept.

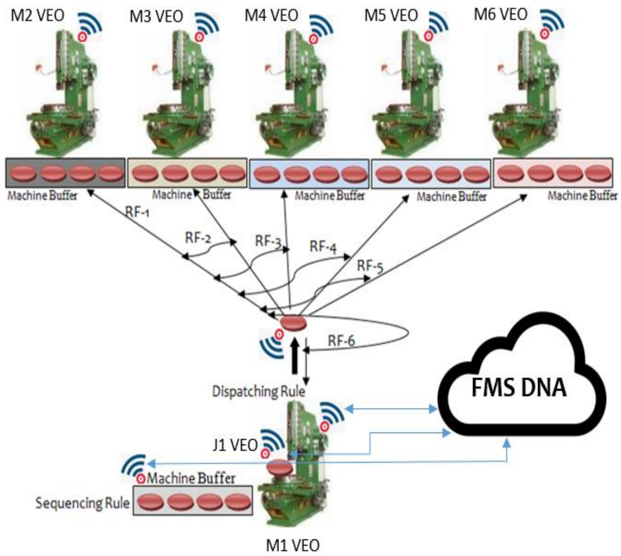

Figure: DDNA based FMS Model

The VEP repository can be queried by the GUI, which makes similarity comparisons with each experience stored and returns the most similar SOEKS. Mechanism for query execution in presented in Figure 7; Euclidean distance is calculated between the query-SOE and each VEP-SOE present in the FMS-DNA repository. SOE with the least value is considered as the best SOE or most similar SOE.

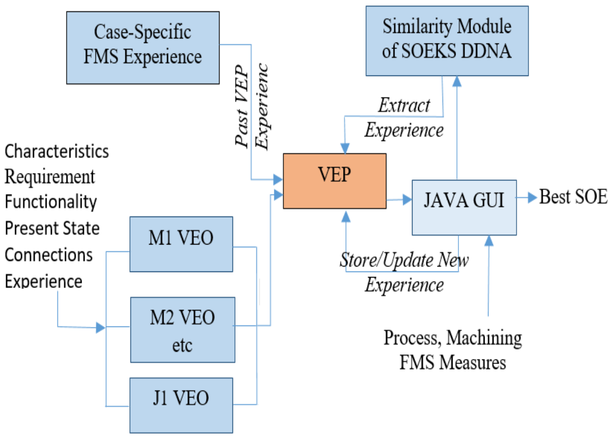

Figure 7: Mechanism for effective decision making

6. EXPERIMENTAL RESULTS

A number of sample queries were executed to find the most similar SOEKS. For example, in query 1, VEP similarity is calculated for a product with RF1 when MST = 4200, cost = 17300, Machine Utilization = 80% and Queue waiting time = 5.3. Figure 8(a) illustrates the outcome of the execution of this query. FMS-DNA returns the top most similar SOEKS which in this particular case is VEP1 having similarity 0.0502. The query also returns the codes of M1-VEO for the most similar VEO-Code. This enables to fetch all the micro level details of Machine 3 at M3-1 code corresponding to most similar VEP- SOEKS. This previous FMS experience of the RF, machines and the jobs can beneficial not only for the design but also in performance evaluation.

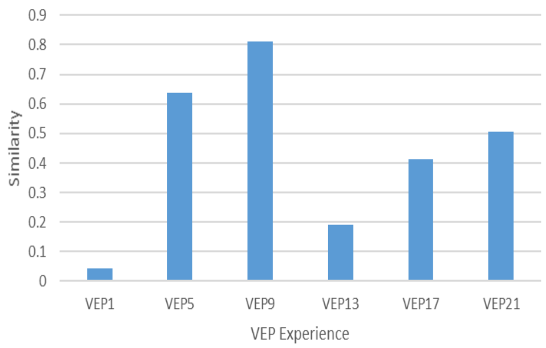

Figure 8(a): Similarity index for query 1 at RF1

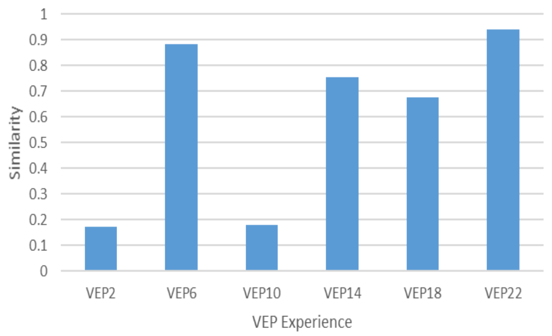

Figure 8(b): Similarity index for query 2 at RF2

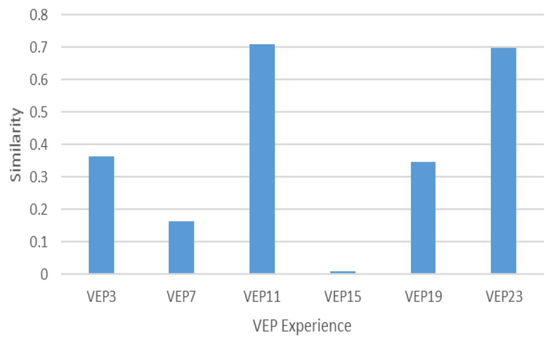

Figure 8(c): Similarity index for query 3 at RF3

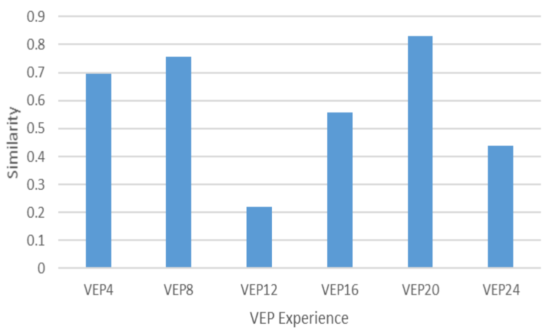

Figure 8(d): Similarity index for query 4 at RF4

Different query 2, 3 and 4 are executed when FMS is executed at RF2, RF3 and RF4 respectively; results are presented in Figures 8(b), 8(c) and 8(d). The output of these queries shows the top most similar VEP experiences along with the experiences of the machines involved. Thus, the entire experience at routing level, machine and job level can be retrieved and can be used to enhance effective decision making and performance evaluation in possible future queries.

7. CONCLUSIONS

Decisional DNA based experience model for a typical FMS is developed, which is capable of capturing and storing formal decisional events both at the process as well as at the object level. Similarity of previous experience is calculated with current requirement. Designing and planning issues of FMS can be solved mainly by this modelling technique. This technique induces intelligence as the database containing information of FMS installation has an interrelation between VEP and VEO features. Moreover, since each component of the FMS has a virtual model and can operate individually and also together with the wider range of production.

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