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Designing Intelligent Factory: Conceptual Framework and Empirical Validation

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Abstract

This paper presents a framework for monitoring, analysing and decision making for a smart manufacturing environment. We maintain that this approach could play a vital role in developing an architecture and implementation of Industry 4.0. The proposed model has features like experience based knowledge representation and semantic analysis of engineering objects and manufacturing process. It is also capable of continuous real time visualization of key performance indicators (KPI's) and supports M2M communications over novel protocols like OPC-UA. Our model covers the industrial manufacturing cycle right from capturing raw data at machine level, converting it into useful information, doing semantics analysis and performs real time KPI visualization.

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Keywords: Virtual Engineering Object (VEO), Virtual Engineering Process (VEP), Set of knowledge Experience Structure (SOEKS), Decisional DNA,, OPC-UA.

1. Background

The unprecedented advancement in the field of information and communication technologies (ICT) is forcing advance manufacturing countries to integrate it with production industry. ICT offers features like connectivity, Artificial Intelligence (AI), industrial automation, etc. which leads to a paradigm shift in production by having interconnected systems that will eventually generate a new industrial revolution[1, 2].

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Apart from IT systems in industries, technologies such as Big Data, Cloud computing and semantics, promise to generate intelligent factory into forth industrial revolution known as Industrie 4.0[3]. The emergence of intelligent factory/Industrie 4.0/ Industrial Inter-net/Factories of the Future as a new wave can transform the production and its associated services. It is a powerful concept which promotes the computerization of traditional manufacturing plants and their eco-systems towards a connected and 24/7 available resources handling scheme. Industrie 4.0 promotes vision of smart factories and is based on the technological concepts of Cyber Physical Systems (CPS) [4]. CPS are central to this idea and are entitled to be part of smart machines, storage systems and production facilities able to exchange information with autonomy and intelligence[5, 6].

This research work proposes a conceptual framework along with a practical architecture to capture data coming from CPS-like devices, infer useful information from it and visualize it in real time. As presented by Shafiq et.al[7], Knowledge engineering plays an important role in cyber physical systems as there is a need for a unified framework to represent the myriad types of data and application contexts in different physical domains, and interpret them under the appropriate contexts[8]. Moreover, this system should be able to decide and trigger actions according to changing manufacturing situations, and for such reason it requires the use of knowledge based and intelligent information approaches. Concept of Virtual engineering object (VEO) and Virtual engineering process (VEP) are used as knowledge representation and semantic analysis tool[9-13].

The structure of this paper is as follows: section 2 describes the conceptual framework for the case study under taken for the implementation of intelligent factory. Experiments conducted and results obtained are presented in section 3 and in the last section conclusions are presented.

2. Framework description

The primary objective of this work is to contribute to intelligent factory concept proposing a model that entails rapid transfer of new knowledge into industrial processes and products. In our work, we focus on the knowledge based conceptual model, architecture and key elements needed for the support of Industrie 4.0. The proposed conceptual framework (see Fig.1) is divided in four stages: (i) Data Collection and Communication platform (ii) Data preparation and healing (iii) Semantic Analysis and (iv) Real-time visualization.

The proposed architecture for intelligent factory can serve to create horizontal value networks at a strategic level, provide end-to-end integration across the entire value chain of the business process level and enable vertically integrated and networked design of manufacturing systems.

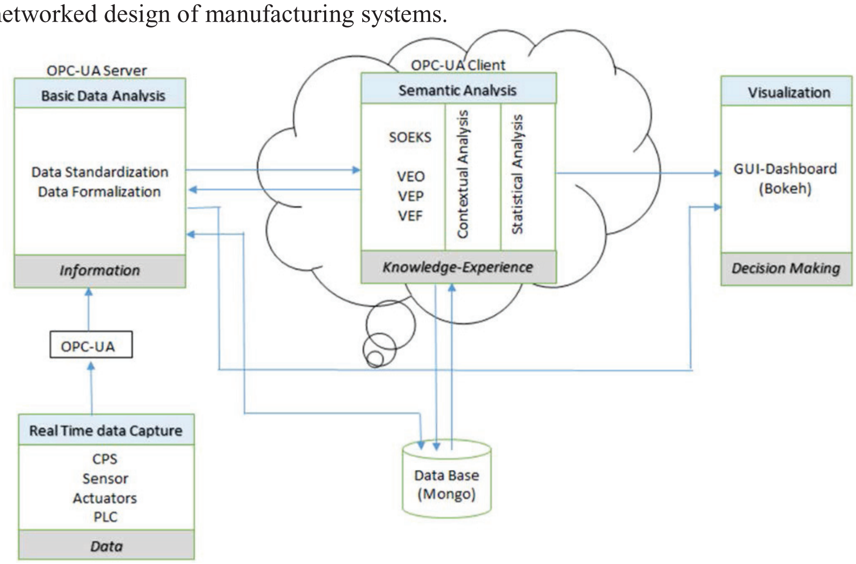

Fig. 1. Architecture for the intelligent factory

2.1 Data Collection and Communication platform

In all industrial applications, data/information plays a very important role. Standardization and languages for standardization of communications in a machine-to-machine context like OPC (Object Linking and Embedding - OLE for Process Control,) and more recently OPC-UA (Unified Architecture), using an unified architecture not dependent on windows OS, play a very important role. The benefits of using the aforementioned approaches are quite evident in the sense that an abstraction layer from the manufacturer's programming interface and proprietary languages in the PLC's, sensors and actuators are simplified acting as an inter-language for communication. The data collection in the OPC-UA approach is representational state transfer (REST) oriented, client-server implemented and provides a mechanism to subscribe to data changes in an asynchronous manner. Data collection then can be serialized and the gathered data stored in different databases that will be implemented as clients consuming the data. Analysis in terms of data changes and event changes are also benefited, as the synchronous/asynchronous need of a given application is a feature that will become easy to handle and maintain.

2.2 Data preparation

Once the data is collected, it is necessary to prepare it for its exploitation. First of all, there is a necessity of some filtering, as not all the raw data is useful. The outliers and any other fragment of data that is considered noise are eliminated here.

Then, the data is standardised. Here we propose the use of AutomatonML[14] which is an open standard based on XML for the storage and exchange of plant engineering information. AutomationML describes real plant components as objects encapsulating different aspects. An object can consist out of other sub-objects, and can itself be part of a bigger composition.

Finally, the data is aligned and synchronized. Since sensors do not normally have a real-time clock, as computers have, it is responsibility of the device that is capturing to set a time reference. Moreover, each sensor has its own sample time that depends on the dynamic of the system that is monitoring. So, all the captured data is organised and rearranged in this module to send it to the cloud in a synchronous pace.

2.3 Semantic Analysis

The semantic enhanced intelligent factory model agglutinates the entire reasoning process. The semantization process starts with an IN/OUT module that synchronizes the information to be enriched with the communication layer messages/serialized-responses maintained between the server and the client. As mentioned in section 1, the sematic reasoner adopted is VEO and VEP.

Virtual Engineering Object (VEO) - Virtual Engineering Process (VEP)

The concept of VEP and VEO can be assimilated with intelligent factory or Industry 4.0[7]. In manufacturing environment, collection of components/tools/objects constitutes a process as depicted in Fig.2. Following this pattern, virtual representation of artefacts in the form of VEO and the process as VEP is developed.

Virtual Engineering Objects (VEO)

A VEO is a knowledge representation of an engineering artefact comprising experience models, domain and functionality along with a physical attachment to the virtual object in its conceptualization. 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 from its inception until its useful life is stored or linked in it. A VEO can encapsulate knowledge and experience of every important feature related with an engineering object. This can be achieved by gathering information from following six different aspects of an object Characteristics, Functionality, Requirements, Connections, Present State and Experience[9, 10].

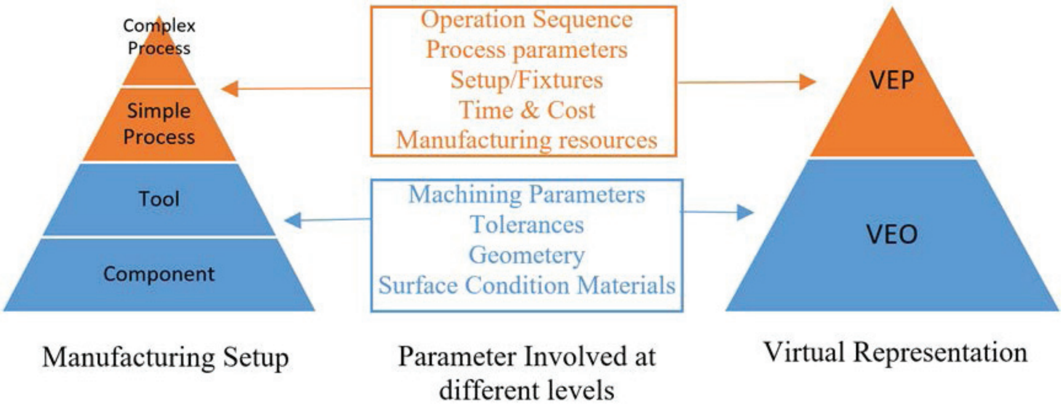

Fig. 2. Correlation between physical and virtual world

Virtual Engineering Process (VEP)

Virtual engineering process (VEP)[11, 13] is a knowledge representation of manufacturing process/process-planning of artefact having all shop floor level information regarding required operations; their sequence and resources needed to manufacture it. VEP deals with the selection of necessary manufacturing operations and determination of their sequences, as well as the selection of manufacturing resources to "transform" a design model into a physical component economically and competitively. In addition to this, for VEP, information of all the VEO's of the resource associated with the process is also linked. Therefore, to encapsulate knowledge of the above mentioned areas, the VEP is designed having the following three main elements or modules (i) Operations, (ii) Resources, and (iii) Experience.

The knowledge representation technique of Set of experience knowledge structure (SOEKS)-Decisional DNA (DDNA) [15] is used for developing VEO and VEP models [9].

2.4 Real-Time Visualization

Visual techniques are increasingly being used for exploratory analysis and to quickly identify patterns in industrial processes. As Visual Analytics are especially suited for complex real world problems with large amounts of data, they fit perfectly in this field. The proposed framework contains a Visual Analytics module that offers a graphical output to the semantically enhanced information stored in the architecture.

In our approach, we propose a flexible dashboard system instead of a single universal visualization. The diversity of problems that can appear in a manufacturing environment is too high to create a unique type of visualization. It is better building an interactive tool that can create customized visualizations. The user can visualize in real time different variables, graphs and charts, and compose its own visualization configuration.

The visualization module is based on Bokeh[16], which is a Python interactive visualization library that targets modern web browsers. Its goal is to provide elegant, concise construction of novel graphics in the style of D3.js (another library for data visualization), but also deliver this capability with high-performance interactivity over very large or streaming datasets.

3 CASE STUDY

3.1 Problem statement

There is a need to develop a knowledge based virtual manufacturing environment in which real time data communication, monitoring, semantic analysis and visualization of KPI can be done in real time over a network. The advantage of this framework will be that it will facilitate effective decision making both at the planning stage as well as at the operations stage; which, in turn, will enhance the manufacturing performance.

3.2 Methodology

A case study is designed to capture data coming from machines, monitor it, analyse it and finally visualize it in real time. Data is collected from four sensors, measuring different parameters: temperature, pressure, spindle-speed and metal removal rate. These are key operation parameters as they affect surface finish, machining time and other output indicators; thus, they must be monitored and analysed. Total number and type of these data sensors may vary according to different machining conditions. The purpose of choosing the above mentioned sensors is to demonstrate the practical applicability of the proposed concept. Some of the salient features of the case study implementation are:

- Using CPS-like devices and OPC-UA to support data capture coming from sensors and actuators recording specific activities of the machines.
- Standardising data representation by using AutomationML.
- Using SOEKS converting machine data stored in database (Offline) as Set of Knowledge Experience Structure (SOEKS).
- Using SOEKS to create VEO and VEP according to their format.
- Plotting streaming data in the client using visualization API based on BOKEH.

3.3 Results

Data capture and visualization

As illustrated in Fig.3, information is continuously being pushed from machines. The foremost role of the model is to manage the incoming data and to store the information in an efficient fashion. Storing streaming data is effective for the evaluation of machine performance and for its maintenance. Any significant change to the status of the monitored machine can be detected. The change can be defined as a dramatic variation (high and low as shown in Fig.3) in machine health value, a maintenance action or a change in the working regime. During the life cycle of a machine, these streaming data will be accumulated and used to construct the time-machine history of the particular asset. This active time-machine record will be used for peer-to-peer comparison between assets. Once the asset is failed or replaced, its relative time-machine record will change status from active to historical and will be used as similarity identification and synthesis reference.

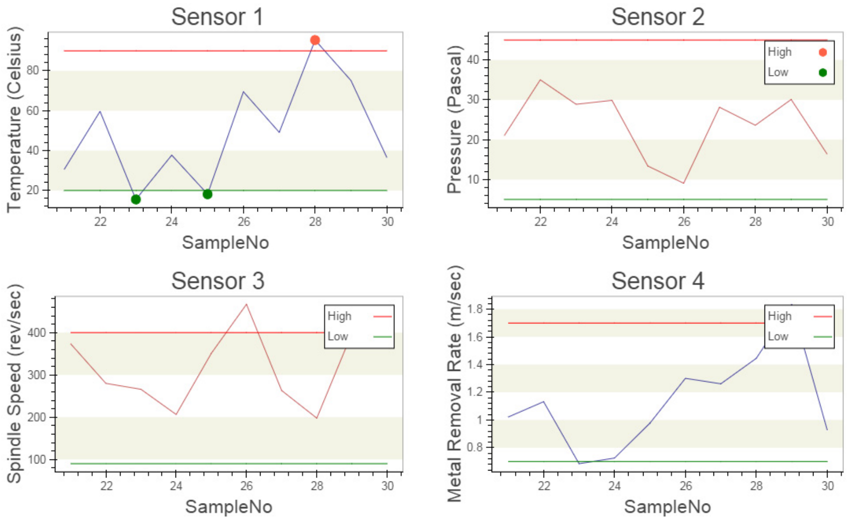

Fig. 3. Visualization of streaming data

Performing semantics on the SOEKS similarity identification

Data coming from four sensors is captured and arranged in the SOEKS format to represent formal decisions taken while operating the machine. To compare the current machine behaviour, similarity with each past SOEKS of the machine is calculated. Similarity index is calculated by Euclidian distance between the variables.

Fig.4 shows similarity index calculated for each SOEKS in the repository with the query SOEKS. The SOEKS marked with a red dot indicates the most similar SOE. Once the patterns are matched, future behaviour of the monitored system can be predicted more accurately.

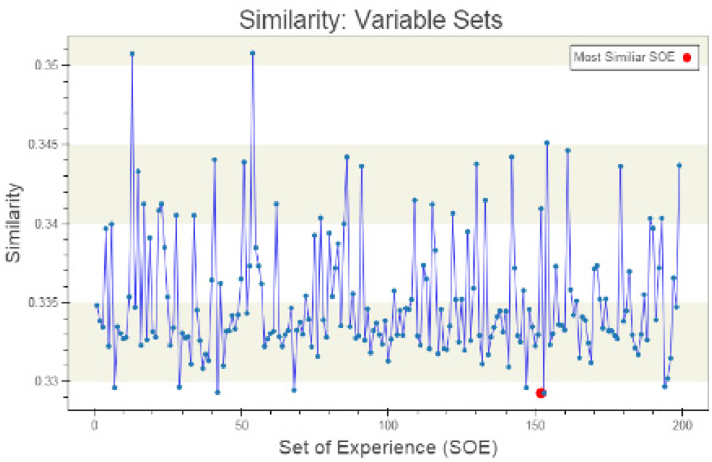

Fig. 4. Similarity identification for each SOEKS

For each set of variables, SOEKS functions to calculate machine health index and tool life are defined. Fig.5 illustrates corresponding machine health index and tool life for each SOEKS. Predicting remaining useful life of assets helps to maintain just-in-time maintenance strategy in the manufacturing plant. In addition, life prediction along with historical time machine records can be used to improve the asset utilization efficiency based on its current health status. Historical utilization patterns of similar asset at various health stages provide required information to simulate possible future utilization scenarios and their outcome for the target asset. Among those scenarios, the most efficient and yet productive utilization pattern can be implemented for the target asset.

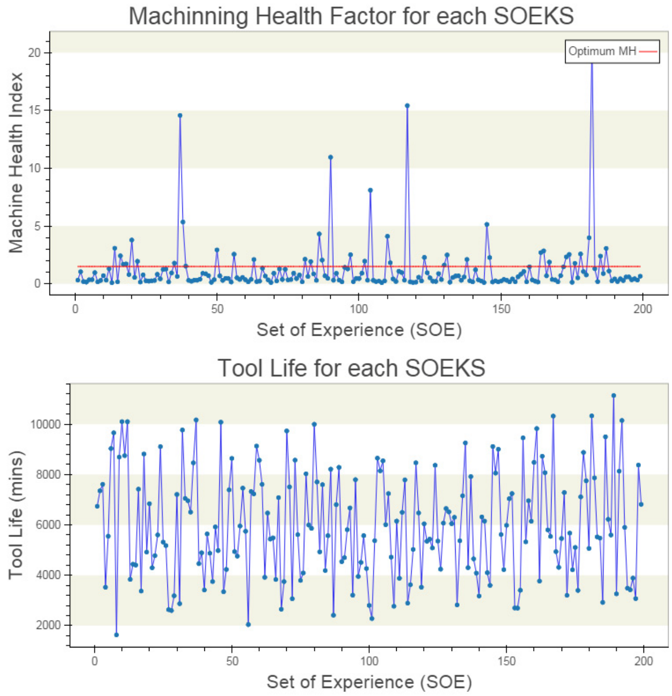

Fig. 5. SOEKS Functions evaluation for each formal decision

4. Conclusions

In this research, a conceptual framework for building intelligent factory is presented. We have also presented a practical implementation of the concept with real sensor data gathered from an actual machine. Intelligent factory holds huge potential as it enables dynamic manufacturing business last-minute changes to production and delivers the ability to respond flexibly to disruptions and failures. End-to-end transparency is provided over the manufacturing process, facilitating optimised decision-making. Therefore, from the presented work, it can be concluded that the proposed framework has features to build intelligent factory effectively; moreover, it has prospects to facilitate building of bigger environments of Industry 4.0.

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