Decisional DNA (DDNA) based Machine Monitoring and Total Productive Maintenance in Industry 4.0 Framework

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Abstract: The entire manufacturing spectrum is transforming with the advent of Industry 4.0. The features of Set of Experience Knowledge Structure (SOEKS) and Decisional DNA (DDNA) were utilized for developing Virtual Engineering Objects (VEO), Virtual Engineering Process (VEP) and Virtual Engineering Factory (VEF), which in turn facilitate the creation of smart factories. In this study, DDNA based Machine Monitoring for Total Maintenance in Industry 4.0 framework is demonstrated. The concept of VEO is used for the Tool and Equipment Monitoring, while for the Plants Operations Monitoring and Quality Monitoring, VEP and VEF are employed. Query extraction feature of DDNA is exploited for Adaptive Control. This study shows that Machine Efficiency (ME) can be monitored along with analysis of machine KPI's like breakdown time, setting time, and other losses. Moreover, reports can be generated efficiency-wise, breakdown-wise, operator-wise. The data of these reports is used to predict and make future decisions related to machine maintenance.

Keywords: Decisional DNA, SOEKS, Machine Monitoring, Total Productive Maintenance.

Introduction

The monitoring and productive maintenance of industrial machines, tools and equipment is essential to support production. There are various maintenance and analytical levels to increase productivity in the complexity of the interactions between production activities in ever-expanding manufacturing environments.

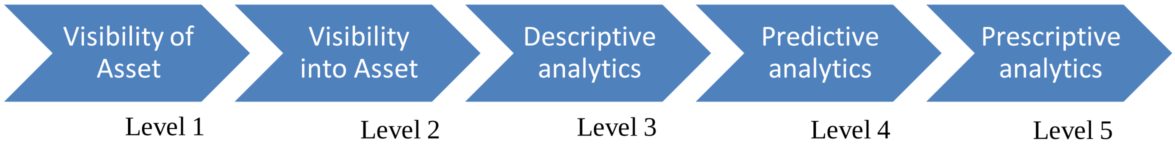

Figure 1: Levels for Total Productive Maintenance

As shown in figure 1, level 1 and level 2 are preparatory levels and generally deal with what the asset is made of up and what are the current values of monitored variables? Descriptive analytics answers the current condition and situation of the machine. Predictive analytics forecasts when a particular event will occur. And finally, prescriptive analytics proposes what decisions/remedial actions should be taken when the event occurs.

In this study, we have demonstrated a mechanism for every level of maintenance with a particular focus on Predictive Maintenance. It has become popular as comprehensive checks to diagnose errors and detect the exact location of malfunctioning using various analyses is provided (Sang *et al.*, 2020). Predictive Maintenance (PdM) is based on models on historical data or past experience.

Improved decision-making for production maintenance can be achieved and the downtime of operations can be reduced, as PdM can forecast trends and behaviour patterns in advance and correlate statistical and machine learning models (Lee et al., 2006; Sezer et al., 2018). Data is the key to this generation of knowledge and information that can anticipate or collaborate in making predictive maintenance decisions.

The advancement of predictive maintenance is evident by the arrival of Industry 4.0. The combination of the Internet of Things (IoT), cyber-physical system, Big data, Machine Learning and the Internet of Systems allows computers to connect each other and do communication that at the end can decide on the system of Industry 4.0 (Jena *et al.*, 2020; Putra *et al.*, 2020)

Implementation of PdM is instrumental in designing and developing the concept of a smart factory or intelligent manufacturing/industry as it increases the manufacturing capabilities and preempts events (Kiangala & Wang, 2018).

Similarly, real-time Machine Monitoring has also been possible with the emergence of Industry 4.0, with the help of sensors, cameras, RFID and other such tools. Not only are the critical health parameters of machines captured, but ambiance monitoring is also achieved. Moreover, predictive control features like system shut down alerts and system maintenance reminders can be added.

In this paper, the concept of VEO, VEP and VEF is applied on the different levels of total Productive Maintenance and machine monitoring; and with the help of a case study DDNA based predictive maintenance is demonstrated.

Predictive maintenance (PdM)

In recent times, with the advent of Industry 4.0, Predictive maintenance (PdM) has been generating a lot of interest among researchers. Various techniques and tools have been proposed to integrate the PdM data acquisition, storage, processing, assessment, security, knowledge development and distribution and security, and artificial inelegance.

In this section, the concepts of PdM identified by researchers are discussed; consequently, the direction of this study is derived. It is reported that upto 15% to 60% of the total manufacturing costs is incurred on maintenance(Haarman et al., 2017; Mobley, 2002). However, the management does not appropriately measure the amount spent related to maintenance. This is the motivation for carrying this study and discovering new techniques to improve manufacturing maintenance.

Data gathered from the various sensors, cameras, RFID’s in Industry 4.0 setup offers new prospects for solutions of life prediction of an engineering object/asset (Yan et al., 2017). The concept that PdM can produce scheduling action built on condition or equipment performance through time becomes promising and even primordial for the Industry's future (Wu et al., 2016). One of the foremost necessities for effective PdM attainment is sufficient data from all aspects of the manufacturing process (Kiangala & Wang, 2018).

As a result, it can reduce downtime and maintenance costs and increase quality and productivity as well. The challenge of predicting the correct Remaining Useful Life (RUL) of an asset is common in automation, mechanics, and engineering applications. For complete industry management, this concept of prediction is a part of Prognostics and Systems Health Management (PHM). In PHM, there are three principal axes:

(i) observation (ii) analysis (iii) action (Zerhouni et al., 2017).

In this framework, research associated to the PdM is directly related to the observation axis of PHM and using intelligent methods to predict the failure (Carvalho et al., 2019).

Some researchers (Iskandar et al., 2015) consider that PdM is subset of PHM components together with Mean-Time-To-Repair (MTTR) and Equipment Health Monitoring (EHM). In maintenance, there are generally four categories of occurrence:

(i) Corrective- corrective maintenance happens when the fault is detected or indications/signs are observed.

(ii) Preventive- In preventive maintenance, schedules are used at specific and predefined times.

(iii) Predictive - PdM utilizes time-based knowledge and information to report a possible failure evading downtime.

(iv) Prescriptive- In prescriptive maintenance it is likely to answer: ‘‘How the occurrence of a specific event can we controlled?’’ or, in other words ‘‘How can an event can be made to happen?’’ by providing useful knowledge for improving and optimizing upcoming maintenance processes and making decisions.

In the PHM, are four kinds of maintenance technics (i) corrective (ii) fixed-interval preventive (iii)failure-finding, and (iv)Condition-Based Maintenance (CBM) (Zerhouni et al., 2017).

Three fundamental classification prediction approaches related to PdM are reported in the literature (Wu et al., 2017).

(i) Physical models – These models are based on mathematical modeling; the main features of these models are to predict the condition of a component, measurement of failure, the precision of the condition status, and statistical methods to limit these indices.

(ii) Knowledge models – These models are based on the methods that decrease the complexity of a physical model. For this purpose, these models are often used as a hybrid strategy, for example, fuzzy logic or expert systems.

(iii) Data models – These models are primarily found in the present development of PdM solutions: pattern recognition, statistics-based or artificial intelligence (AI), and models based on machine learning (ML) algorithms.

In addition to the classifications cited above, other hybrid definitions are also found, for example: Cloud-based (Kiangala & Wang, 2018; Wu et al., 2017), Deep Learning-Based (Yan et al., 2017), IoT Based, Fleet-based, Time-Based (Wu et al., 2017).

Some of the challenges that are idenfied from the review presented above for achieving reproducibility and high-quality results associated with predictive maintenance are

(i) propose a taxonomy for predictive maintenance in the Industry 4.0 framework.

(ii) Organize the main concepts related to predictive maintenance

(iii) present the main general-purpose and flexible predictive and machine monitoring models applied to Industry 4.0.

To provide solutions to the above-mentioned challenges, the concept of VEO, VEP and VEF is proposed and discussed in the next section.

VEO-VEP-VEF

A VEO is a knowledge representation of the engineering artefact along with its experience embedded in it. The goal of VEO is organize experience of engineering object in a flexible standard format, thus converting it into useful information that can help practitioners to better focus on solving the problems at hand, without spending undue amounts of time gathering information, modelling the information, and then analysing it. Set of Experience Knowledge Structure (SOEKS) and Decisional DNA (DDNA) (Sanin, 2008; Shafiq et,al 2014) a smart knowledge based decision tool is used for developing VEO. That means a VEO is not only be a knowledge repository but it has SOEKS-DDNA qualities like self-awareness and reflexivity embedded in it. A VEO can formally be defined as:

A VEO is knowledge representation of an engineering artefact, it has three features: (i) the embedding of the decisional model expressed by the set of experience, (ii) a geometric representation, and (iii) the necessary means to relate such virtualization with the physical object being represented.

The scaled up version of VEO is VEP and VEF; VEP is KR at process, planning and shop floor level including associated VEOs in it while VEF is KR at factory or system level encompassing VEOs and VEPs within. The prospects for applying concept of virtual representation to manufacturing is very promising as offers a systematic approach to capturing, storing, distributing, and reusing information in order to make it available, actionable, and valuable to others. This approach will help the practitioners in effective decision making at every stage involved in manufacturing based on the past experience, which in turn will enhance industrial design and manufacturing (Shafiq, 2015; Shafiq, 2016; Shafiq, 2018).

DDNA based Machine Monitoring and Analytics for Total Preventive Maintenance

The entire manufacturing footprints can be captured through VEO-VEP-VEF. As the figure 2 shows that the virtual representation of resources in VEO, process is VEP and Factory is VEF. Figure also depicts that the features of Machine Monitoring and Total Preventive Maintenance can also be represented virtually by VEO-VEP-VEF according their level in the manufacturing pyramid.

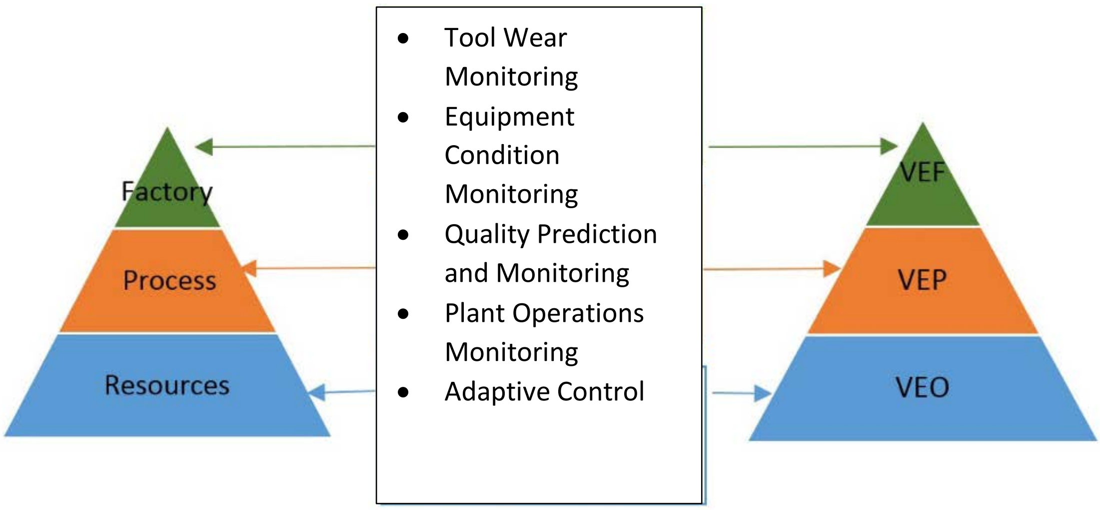

Figure 2: VEO-VEP-VEF based Machine Monitoring and Total Preventive Maintenance

First, VEOs of the machines required to produce the engineering component are developed. Then, the VEP to produce an engineering component is built based on the case specific experiences of that manufacturing unit. Finally, VEF having all the factory level knowledge along with links to VEP and VEO is constructed. VEOs along with experience of engineering process (VEP) form an experience repository of a manufacturing unit. Table 5-1 demonstrate the structure of VEF.

CSV files storing formal decisions related with VEO-Tool Wear Monitoring, VEO-Equipment Condition Monitoring, VEP-Quality Prediction and Monitoring, VEP-Plant Operations Monitoring, VEF-Adaptive Control were made. Having these files in the CSV format, a parser is written in Java programming language to read this information, convert this into SEOKS and create Productive Maintenance-DNA (pdmDNA). Once the pdmDNA is constructed, decisional DNA has feature that it can queried.

Similarity index can be calculated between the $querySOE_j$ (SOE made up of query) and the sets of experience $pdmDNA_i$ (entire pdmDNA). The Euclidean distance has been selected as a measure of similarity, the equation is:

$$S_V\left(pdmDNA_i, querySOE_j\right) = \sum_{k=1}^{n} w_k \left[\frac{\left|pdmDNA_{ik}^2 - querySOE_{jk}^2\right|}{max\left(|pdmDNA_{ik}|,|querySOE_{jk}|\right)^2}\right]^{0.5} \quad \forall k \in pdmDNA_i \wedge querySOE_j$$

$pdmDNA_{ik}$, $querySOE_{jk}$ are the k^{th} attribute of the sets $pdmDNA_i$ and $querySOE_j$, w_k is the weight given to the k^{th} attribute, in this case, variable; and n is the number of variables on $pdmDNA_i$.

When query is generated through a GUI, it is converted into a query SOEK (*querySOE* of equation 1) programmatically. Depending upon whether it is related with the object, process or the factory level, program will keep on calculating the similarity of query SOEK with each of the SOEKS stored in the pdm*DNA*. Finally, similarities calculated are sorted and the top most similar SOEKS are returned.

Results

Once the data acquisition of the KPI's of machine monitoring is done, data is processed and real time monitoring is done on possible. Figure 3 shows a sample dashboard of a manufacturing setup, where data visualization KPI's are presented. Normal operating limits are parameters are defined and in case of any abnormalities, alerts are raised, so that corrective measures are taken to avoid any major losses. The logs of the machine parameters are also analyzed for patterns and trends to predict and prescribe maintenance measures.

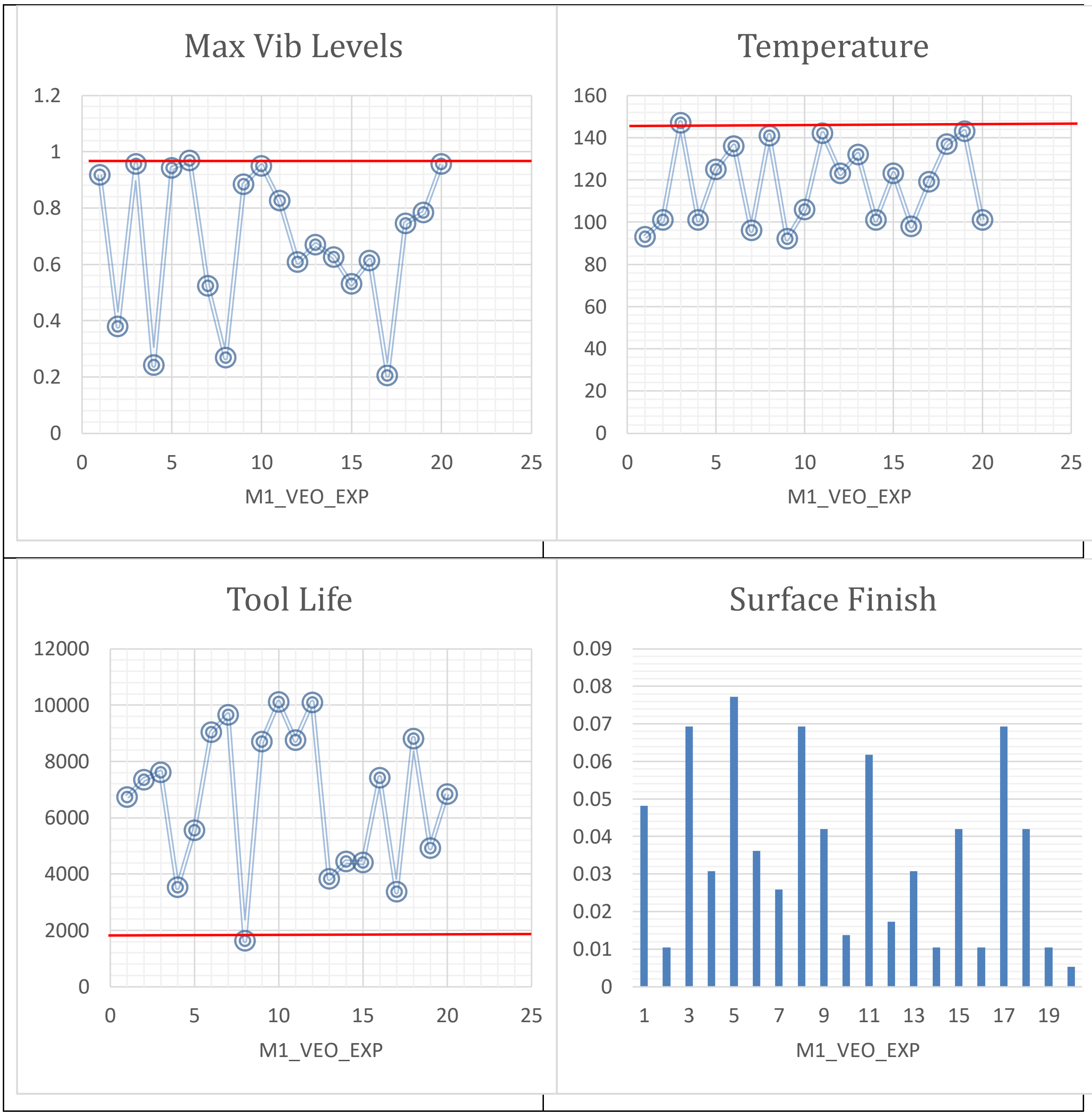

Figure 3 Dashboard for real time Machine Monitoring

In the VEO-VEP-VEF framework linkage of the different levels is from top to bottom i.e. VEF will have linkages of VEP and VEO. Similarly, VEP will have linkage of VEOs whereas VEOs will not have any connections with VEP and VEF. There are two methods of calculating the similarity-identification. First is the actual combined experience that occurred at each level in that manufacturing unit. And the second method is to find most suitable experience individually at each level and then by combining the similarity-identification through Phenotyping create a new virtual experience for the entire factory.

For this case study most suitable experience individually at each level is demonstrated. The query structure, the levels through which it can be executed as well as the structure of solutions are shown in Table 1. *Query* has SOEKS variables only of VEO, *Result-1* show experience at object level i.e. VEO_Exp.

Table 1 Query and result structure

Sample Query Structure	**Query level**	**Sample Test Query**	**Result Structure**
Query = (Depth of Cut, Speed, Feed, Vibration Level, Temperature, Tool Life, Performance, OEE)	VEO	(Depth of Cut = 50, Speed = 450, Feed = 1.5,Vibaration levels Tool Life = 7600)	VEO_Exp = 3

Table 1 illustrates the mechanism to achieve a result with respect to a query. For the sample test query, the solution is as follows:

Forecast for predictive maintenance can be achieved through this framework. Knowledge of the machine (M1) is stored in the SOEKS format as shown in table 2 and machine maintenance KPI’s like Vibrations level, Surface Finish, Tool Life, Performance and Overall Equipment Effectiveness (OEE) can be queried through

DDNA. As per the query, the Max Vibration levels and Tool Life of Machine (M1) at a specific machining parameters Depth of Cut = 50, Speed = 450, Feed = 1.5. is calculated based on the previous experience of the machine. From the past experience it is calculated that for the given conditions the closest past experience available is VEO_Exp = 3 and the corresponding Max Vibrations Level is 0.956 and the Tool like is 7612.62.

The benefit of using this approach is that each level of the framework can be treated as independent phase and according to requirement best experience be selected. These independent SOEs are combined together to create a new virtual experience. Thus, providing more options to the practitioners for effective decision making.

Table 2 Sample SOEKS format for VEO

VEO Input Variables							**Output Variables**			
VEO_Exp	**Machine**	**Depth of Cut**	**Speed**	**Feed**	**Max Vib Levels**	**Temp**	**Tool Life**	**Surface Finish**	**Performance**	**OEE**
1	M1	47	459	1.5	0.918	144	6739.69	0.0481125	0.7561	0.57
2	M1	48	190	0.7	0.38	144	7354.06	0.0104778	0.8306	0.496
3	M1	51	478	1.8	0.956	123	7612.62	0.0692820	0.4746	0.742
4	M1	38	121	1.2	0.242	132	3522.13	0.0307920	0.903	0.412
5	M1	46	471	1.9	0.942	115	5551.02	0.0771938	0.7545	0.718
6	M1	52	484	1.3	0.968	132	9031.61	0.0361378	0.7126	0.407
7	M1	55	262	1.1	0.524	110	9657.69	0.0258738	0.3791	0.778
8	M1	35	134	1.8	0.268	137	1629.25	0.0692820	2.0776	0.663
9	M1	52	442	1.4	0.884	100	8694.76	0.0419113	0.6069	0.678
10	M1	53	475	0.8	0.95	141	10102.6	0.0136853	0.6969	0.772
11	M1	54	413	1.7	0.826	104	8751.62	0.0617978	0.8477	0.434
12	M1	55	304	0.9	0.608	134	10099.8	0.0173205	0.4321	0.768
13	M1	37	335	1.2	0.67	145	3835.56	0.0307920	1.2738	0.464
14	M1	37	313	0.7	0.626	137	4436.90	0.0104778	0.7501	0.66
15	M1	41	265	1.4	0.53	99	4404.83	0.0419113	0.7561	0.427
16	M1	47	307	0.7	0.614	96	7420.59	0.0104778	0.8313	0.625
17	M1	42	103	1.8	0.206	129	3370.71	0.0692820	1.0227	0.386
18	M1	53	373	1.4	0.746	112	8816.12	0.0419113	0.6076	0.659
19	M1	38	392	0.7	0.784	127	4919.56	0.0104778	0.5803	0.637
20	M1	43	478	0.5	0.956	94	6842.26	0.00534	0.5734	0.759

Conclusion

Knowledge representation technique of Decisional DNA is employed for total preventive maintenance. The concept VEO, VEP and VEP is utilized to create knowledge models of various modules of preventive maintenance like Tool Wear Monitoring, Equipment Condition Monitoring, Quality Prediction and Monitoring, Plant Operations Monitoring and Adaptive Control. Results show that this approach is useful in real time remote machine monitoring and visualization. Furthermore, DDNA empowers the models to predict the preventive measures based on the past experience of the environment. This approach will facilitate in effective and efficient future machine monitoring and total preventive maintenance decision making. In future many more features of maintenance can be studied like the machine ranking and operator ranking. Moreover, interactive visualization capabilities can also be integrated in these models.

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