Artificial Intelligence Based Maintenance Framework for Industrial Machinery

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Artificial Intelligence Based Maintenance Framework for Industrial Machinery

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ABSTRACT

With the constant evolution of e-manufacturing technologies, there is a clear trend for e-maintenance that involves the integrating of ICT (Information and communication technologies) within the maintenance strategy. This leads to highly sophisticated and complex machinery, which increases the demand for expertise. Unfortunately, a company could always lose the expertise due to experts' retirement, change of occupation or death. This motivates us in this work to develop an e-maintenance model that enables organizations to exploit expert's knowledge in the process of machine fault diagnosis. This paper focuses on the building of a Knowledge-Based System (KBS) in order to capture the experts' knowledge to be permanently kept and cannot be disparaged due to lack of practice. An optimal AI-based tool is proposed that aims at accurate values to retrieve information from KBS, which describes the alarms to diagnose the failure of the machine. An accurate analysis is carried out that yields insight into the impact of KBS on the ability of fault diagnosis. The results illustrate the high-performance of the proposed approach in handling the KBS's data associated.

Keywords:

Maintenance engineering, Predictive maintenance, Artificial intelligence, Agent-based modeling, Machine intelligence, Condition monitoring, Computerized monitoring, Decision support systems

1. INTRODUCTION

Artificial Intelligence (AI), the goal of AI is to develop machines that behave as though they were intelligent. As well as, AI has the goal of solving difficult and complex practical problems which are surely too demanding in industrial sectors. On the other hand, AI is the ability of digital computers or computer-controlled robots to solve problems that are normally associated with the higher intellectual processing capabilities of humans. The subject of AI has been enriched with a wide discipline of knowledge from Philosophy, Psychology, Cognitive Science, Mathematics and Engineering. Therefore, it would admit for example, a computer with large memory that can save a long text and retrieve it on demand displays intelligent capabilities, for memorization of long texts can certainly be considered a higher intellectual processing capability of humans. According to this capability, then, every computer is an AI system. In a nutshell, artificial intelligence is the study of how to make computers do things at which, at the moment, people are better. Tasks such as the execution of many computations in a short amount of time. In this regard AI programs are being extensively used in the maintenance of general-purpose industrial machinery starting from commonly occurring malfunctions to rarely occurring emergency situations. The AI approach is promising for this domain as; it captures efficiency of problem-solving expertise from the domain experts; guides the human operator in very rapid fault detection; explains the line of reasoning to the human operator and supports modifications; and improvement of the process knowledge as more and more experience is gained. Relatedly, AI tools are software-implementations for expert systems knowledge or knowledge-based systems, which apply essential knowledge about some specific areas. The main contributions of this paper in addressing these challenges can be summarized as follows:

- Developing a Knowledge-Based Maintenance (KBM) model for achieving e-Maintenance with machinery fault detection and diagnostic techniques.
- The new model proposed enables us to develop an algorithm that utilizes the appropriate service to satisfy the data matching approach. Based on the model presented in this work, an optimal AI-based tool is proposed, which aims to retrieve the permanently stored information from KBS associated.
- Performing extensive experimental studies to examine the performance of this algorithm. The investigations are shown in PROLOG as a Logic Programming Environment (LPE), by which the proposed algorithms can be significantly implemented and monitored as well as the accuracy of the proposed algorithm in matching the data is also settled.

The rest of the work is organized as follows. Section 2 shows the importance of Knowledge-Based systems in e-

Maintenance. Section 3 introduces literature review and description of existing algorithms for comparison. Section 4 and 5 discuss the usability of the Knowledge-Based approach for achieving e-Maintenance and present an explanation of the real influence on maintenance and the methods that are used to solve it. The system model and objective together with the description of the proposed algorithm that is used for e-Maintenance are shown in section 6. The AI-tool developed, the results of the proposed algorithms and comments on the results are presented in Section 7. The concluding of this work and remarks as well as comments on possible future works presented in Section 8.

2. KNOWLEDGE-BASED SYSTEMS

We now move on to considering the mechanism through which a knowledge-based system of the raw data could be built. In other words, an agent is a program that implements a mapping from perceptions to actions, the agent must be able to rely on a large amount of information and is meant to do a difficult task, programming the agent can be very costly and unclear how to proceed. Here AI provides a clear path to follow that will greatly simplify the work. First, we separate knowledge from the system or program, which uses the knowledge to, for example, reach conclusions, answer queries, or come up with a plan. This system is called the inference mechanism. The knowledge is stored in a KBS. Acquisition of knowledge in the knowledge base is denoted Knowledge Engineering and is based on various knowledge sources such as human experts, the knowledge engineer, and databases. In Figure 1 the general architecture of KBS is presented.

KBS represents a relatively new programming approach and methodology that has evolved and is still evolving for effective plant maintenance management. The most prevalent application of KBS's, which emerged in recent times, has been the fault diagnosis and troubleshooting in maintenance management of industrial machinery. KBS expert systems are being developed to give to the engineer the necessary expertise to solve problems in a specific topic. It has primarily been used in applications like weather, military, medical, network, electrical, electronic and software diagnosis, mechanical, etc. The term KBS is used instead of an expert system to focus attention on the knowledge stored by the system rather than the question of whether or not such knowledge contributes expertise. To do so, the work presented here is based on artificial intelligence techniques that are implemented to easily and quickly build expert systems. This process is named as Machine Learning (ML) and there are a great number of software tools in the market which help the users to efficiently build a real KBS. With KBSs, acquisition of knowledge from human sources, knowledge representation in a machine and its utilization has attained high importance. In the proposed model, Knowledge denotes a more complex term than Data because Knowledge consists of concepts, objects, relationships and inference rules, in specific areas. An expert-knowledge is represented by conditional statements in a natural language. Knowledge processing is an important activity in intelligent systems. In KBSs, the problem-solving knowledge

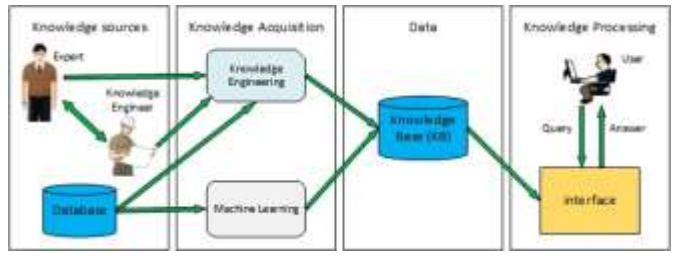

Figure 1 Structure of knowledge-processing systems (KBSs).

of an expert is often represented in terms of [1]:

$$IF\ < Situation > \ THEN\ < ACTION > \ RULE$$

KBS for fault diagnosis and troubleshooting can locate the fault by comparing the enclosed rules in the knowledge base with the data input. When the fault is determined this kind of expert system gives guidelines to the engineer to repair the faulted part of the equipment. In the proposed model the KBS is used to collect accumulated expertise related to a specific industrial field, or to be represented in a modular mode, for easy use and managed by engineers. The proposed framework that is being used in such systems is that of rule-based expert systems. In such systems, expertise of an expert is automated in the form of inference rules of the form [2]:

$$IF < E_1 >; < E_2 >; < E_3 > \ldots; < E_n >;\ then < H >;$$

Where Ei's are part of approved cases or symptoms and H indicates the hypothesis or conclusions. The set of rules that constitute the knowledge base of the rule-based expert system. Another important component of a KBS is an inference engine that uses the given knowledge base in problem solving. In this work, a feasible way to model this problem is proposed, which enables us to implement a tractable framework depends on the knowledge gained concerning the effective machine factors such as voltage and frequency levels, mechanical vibration, temperature rise, noise levels associated with industrial machinery to diagnose the machines' fault and the problem-solving process.

3. LITERATURE REVIEW

Several papers have been published in the past decade on fault diagnosis and repair strategies using various frameworks, concepts, simulation for modeling theory, and the use of expert systems and KBSs in various international journals and conferences. The works of Wang et al. [3], Jardine et al. [4], Tao et al. [5], Rastegari et al. [6], Ahmad et al. [7], Lee and Scott [8], Veldman et al. [9], Derigent et al. [10] and Koochaki et al. [11] were addressed maintenance dependent condition-based policies. Iung et al. [12], Bousdekis et al. [13], Lee J et al. [14], Chiang et al. [15], Zhao et al. [16], Gupta et al. [17], Yang et al. [18] and Alrabghi et al. [19] were focused on the development of maintenance models for evaluation and optimal throughput. The works presented by Lin et al. [20], Visser et al. [21], Alabdulkarim et al. [22], Babaei et al. [23], Voisin et al. [24] and Oladokun et al. [25] have shown that the discrete-event

simulation study could be done through system dynamics, artificial intelligence, neural network, genetic algorithm and knowledge-based expert. Many researchers such as Wang et al. [26], Campos et al. [27] and Das et al. [28] have developed various maintenance technologies that show the e-maintenance platforms that utilize the internet based on web technology, sensor application, wireless and mobile communications for solving maintenance problems. Instances of these systems are the use of the Internet of Things (IoT) items that are embedded with electronics, software, sensors, actuators, and network connectivity to collect and exchange data.

Diogo Cardoso and Luis Ferreira [29], Ruonan Liu et al. [30], Ilesanmi Daniyan et al. [31], Ioannis Mallidis et al. [32], and Abdul Rahman et al. [33] have presented a maintenance with the utilize of machine learning. With the persistent improvement of the Fourth Industrial Revolution, through IoT, the advances that utilize artificial intelligence are advancing.

4. Knowledge Base for Maintenance

The knowledge base is a centralized repository for information

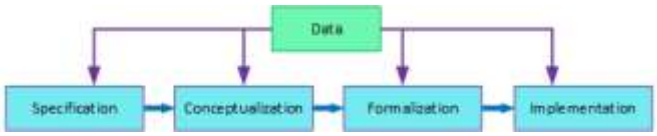

Figure 2 The ontology development process.

such as a library, a database of related information about a specific domain, and creating a logic model from the problem-solving of an expert having enough experience in the domain could be considered as an example of knowledge bases. In industrial-knowledge management systems, a knowledge-base is used to optimize information collection of most of the electrical and mechanical problems associated with industrial machinery and retrieval for identifying machinery measurement, or for a solution of a problem. With the growth of wide area communication networks, we have witnessed the increasing deployment of a variety of KBS's over the last few years. These extensions significantly lead the knowledge base not to be a static collection of information, but a dynamic resource that may itself have the capability to learn. In Industrial-Information Technology (IIT), a knowledge base is a machine-readable resource for the dissemination of information, generally online or in a storage technique that could be placed online. Subsequently, depending upon this stored information about particular machines an engineer can use this information for fortnightly and monthly measurement of other machines. In this work as have already said, AI tool is a vital step in the development of an expert maintenance-support system. Before presenting the KBM model and AI tool for building the expert maintenance support system we describe the maintenance problems.

5. Maintenance Problems Definition

In this section, a description is presented for the common maintenance problems that led to the development of more powerful KBS's for maintenance management, which can be summarized as the following.

- Producing complex machinery that involves a big technical data, maintenance guide and an expensive technology.
- The industrial firms can always lose their expertise because of experts' retirement, death, or change of job. Whilst, KBS accumulates the experts' knowledge, hence is loaded into the system.
- The Knowledge can be captured, permanently available and does not affect by the use or disuse. Whereas, human maintenance expertise can be affected because of the lack of practice.
- Artificial intelligence-based maintenance yields more regular results than obtained through human expertise. A KBS is not susceptible to fatigue, forgetfulness, etc.

KBS's are less expensive than the costs of human experts.

6. Model Development

In this paper, we present a perfect Knowledge-Based Maintenance model based on the knowledge gained regarding the voltage and frequency levels, vibration factor, temperature rise, noise levels in comparison with their regular states in a machine. The major aim of carrying out this research is to design and implement a comprehensive maintenance framework based on the above factors that will address a big database regarding e-diagnostics of any kind of general-purpose industrial machinery. For this purpose, we developed an AI tools like knowledge base systems or expert systems. The following steps have been applied in this scheme, by which the proposed approach is achieved:

6.1 Concept Study & Specifying Responsibilities

In this implementation strategy, a little effort must be taken into account by the industrial firm on exploring and examining the technical aspects that can be very helpful to assess the technical feasibility of implementing KBM. In this step, appropriate indicators are determined, studying the technical options intended to reduce the maintenance cost and production losses, the recognition of machine functions at the workstation, then collecting and formulating machine data to be appropriate to the Knowledge Based designated for maintenance. Furthermore, experiences from the concept study illustrate the significance of place plan to avoid major damages and for maintenance at a time that does not affect production.

6.2 Knowledge Acquisition & Knowledge Engineering

In order to implement knowledge-based maintenance, Knowledge acquisition (KA) is a crucial step in developing knowledge based or expert system maintenance. KA involves knowledge extraction, knowledge analysis, and knowledge representation. We note that traditionally, during an expert interview and gathering observation the knowledge on a specific maintenance field can be widely obtained. Alternatively, the knowledge engineer can acquire the knowledge from relevant maintenance documents and manuals. Next, the raw data collected on this domain can be analyzed and formulated into a knowledge or conceptual model, which then

provides the basis for constructing an expert maintenance system. Notably, this knowledge is often domain-specific, and primarily heuristically based. Therefore, Ontological Engineering (OE) [34] is needed for specification, conceptualization, formalization and implementation knowledge obtained. Figure 2 illustrates the ontology development process. According to these objectives, the OE is applied for achieving three criteria.

First, the chosen model must be easily understandable and must accurately reflect the knowledge specified by the experts. Second, the ontology must be easily extensible. Third, the ontology must be easily integrated entirely or partially with other ontologies. Consequently, the knowledge can be shared and reused among systems, and enhances long-term efficiency of constructing knowledge-based systems in a distributed environment. It is important to mention here that at the requirements of knowledge specification, the technical terms should evidently be studied from more than one viewpoint: from the general viewpoint, which is concerned with specifying the name and symbol of the technical term among other properties; from the engineering viewpoint, which is concerned with defining engineering properties; from the viewpoint of the physical environment. Any taxonomy built should enable a technical term defined from the expert viewpoint to inherit the name and the symbol that are defined for that technical term from the general viewpoint. Clearly, the development process of an ontology is difficult and requires a detailed analysis of the domain.

6.3 Maintenance Coefficient

In this work, the maintenance process is considered maintaining the machine to work in proper condition. For doing this, periodic diagnosis should be applied on a parameter vector θ_j of equipment q, $where\ j = \{1, 2, \ldots, n\}$. For convenience, the set of machine parameter voltage, frequency, mechanical vibration, temperature rise, and noise levels are defined as $vo^j, fr^j, vb^j, tm^j, ns^j$ sequentially.

$Where\ \langle vo^j, fr^j, vb^j, tm^j, ns^j, \ldots\rangle \in \{\theta_j\}$. Then, we have the following definition.

$Definition$ 6.1: $\forall\, q\ \exists\ \theta_j,$
$where\ \langle vo^j, fr^j, vb^j, tm^j, ns^j\rangle \in \{\theta_j\}.$

Next, assume that the values of $vo^j, fr^j, vb^j, tm^j, ns^j\ equal\ to\ 0\ or\ 1$. For example: $vo^j = 0$ that defines the normal state, whereas $vo^j = 1$ defines an abnormal state for this parameter of q. Let Mq a maintenance process on an equipment q. Observe that θ_j is a base vector in the presented model. Thus, we conclude that, as Mq or could be denoted as $\left(M_q^{\theta j}\right)$ can represent the maintenance process based on θ_j. Then, we have the following definition.

$Definition$ 6.3: $\forall\, q\ \exists\ \left(M_q^{\theta j}\right).$

Table 1: Parameter formulas for θ_j

θ	vo	fr	vb	tm	ns	Ar_n	Alarm Description in KBS
0	0	0	0	0	0	x00000	
1	0	0	0	0	1	x00001	
1	0	0	0	1	0	x00002	
.	.	.	.	.	.	.	
.	.	.	.	.	.	.	
.	.	.	.	.	.	.	
1	1	1	1	0	1	x00029	
1	1	1	1	1	0	x00030	
1	1	1	1	1	1	x00031	

Next, we evaluate the probability of success (P_{OS}) of maintenance $\left(M_q^{\theta j}\right)$, which determines the ability of fault diagnosis relying on related KBS. The probability is given by

$$P_{os}\left(M_q^{\theta j}\right) = 1 - P_{of}\left(M_q^{\theta j}\right). \qquad (1)$$

where P_{of} is the probability of failure. The probability formula shown above asserts that $\left(M_q^{\theta j}\right)$ is the dominant factor. Clearly, each possible action of $\left(M_q^{\theta j}\right)$ can be achieved on different values of θ_j. To address this issue, now the technical data kept in θ_j is analyzed, however the kind and precision of this data will deterministically affect directly on $P_{os}\left(M_q^{\theta j}\right)$. As discussed before, the parameter map of θ_j are noted in Table 1, where Ar_n reverts the alarm number and the specification saved in KBS related to the machine, which indicates further details linked to the error alarm.

Before delving into the details, we should note that the θ may result 0 or 1 in conjunction with the Ar_n code number retrieved from KBS that describes the alarms and helps to diagnose the failure on the machine. On the other hand, we note that the alarm description and the available knowledge about the optimal manner to remove the effect can necessitate the taking into account two essential aspects in calculating of $P_{os}\left(M_q^{\theta j}\right)$, which are the detailed explanation about the alarm saved on KBS in addition to the Ar_n code number. Observe that, in many practical scenarios, KBS can broadly affect $P_{os}\left(M_q^{\theta j}\right)$. Let $P\left(M_q^{\theta j}\right)$ is the probability of getting an Ar_n code number about the equipment q from the KBS associated. Consider $P(KBS)_q$ be the probability of getting a maintenance-state description from the same KBS associated. Furthermore, $P\left(M_q^{\theta j}\right)$ is a subset of $P(KBS)_q$. Clearly, the occurrence of $P(KBS)_q$ is necessary to imply the occurrence of $P\left(M_q^{\theta j}\right)$, which can be represented as $P\left(M_q^{\theta j}\right) \subset P(KBS)_q$. Hence, it could be denoted as

$$P\left(\left(M_q^{\theta j}\right)\middle| KBS\right) = \frac{P\left(M_q^{\theta j}\right) P(KBS)_q}{\left(M_q^{\theta j}\right)}. \qquad (2)$$

where $P\left(\left(M_q^{\theta j}\right)\middle|KBS\right)$ is the probability of getting a positive maintenance description, which includes a maintenance-state description and Ar_n code for a number of maintenance cases, consequently $P\left(M_q^{\theta j}\right) \leq P(KBS)_q$. Thus, we conclude that, $P_{os}\left(M_q^{\theta j}\right) = P\left(\left(M_q^{\theta j}\right)\middle|KBS\right)$. We can then approximate (1) as

$$P_{os}\left(M_q^{\theta j}\middle|KBS\right) = \frac{P\left(M_q^{\theta j}\right) P(KBS)_q}{\left(M_q^{\theta j}\right)}. \qquad (3)$$

Needless to say, we can obtain good results with the increasing number of elements in the vector θ_j. Because it would push up the probability of getting the event $P(KBS)_q$ and $P\left(M_q^{\theta j}\right)$. Therefore, we need to apply the concept of redundancy in using sensors to reach this aim. Consequently, we should bear in mind the redundancy yields that the system must use a wide KBS in order to reach an effective diagnosis.

7. Software Development & Evaluation

This scheme is implemented on SWI-Prolog 5 [35] as an AI tool to evaluate the performance of the KBM scheme. The parameter values of the Boldrini-Flanger machine model RIB030EL6000 are measured and monitored. Five different machine parameters were used in the proposed KBM system: (1) voltage, (2) frequency, (3) mechanical vibration, (4) temperature rise, and (5) noise levels associated with the machine to diagnose fault or to warn of an expected fault.

7.1 KBS Algorithm

After completing the technical assessment process for the input parameter values, the KBM system runs a maintenance analysis and comparison of parameter values directly received from sensors with the KBS associated. For the sake of accurate technical analysis and comparison, the attended KBS should contain a wide technical data of the typical parameter values, as well as, it should be provided by the expert and machine manufacturers in the same domain. Once analysis has been carried out, in the case of a positive analysis the KBM system indicates the alarm consists of an alarm number and an alarm description message. Otherwise, it is necessary either to point out an ambiguity state due to the KBS weak or a normal machine data. The pseudo-code for the KBM system is provided in Algorithm 1. As shown in Table 1, the alarm description message returns the KBSs content to describe the situation of the machine on the basis of active alarm(s), which enables the intended target engineers to evaluate the error and respond accordingly. Furthermore, there are three descriptions provided by KBM: alarm explanation, response, and remedy manners to eliminate the causes of this alarm to reach the normal state for avoiding the risk that may occur as well. Figure 3 shows an implementation window of KBM tool.

Besides, to satisfy the accurate control on KBS made, we performed configuration process through the following activities:

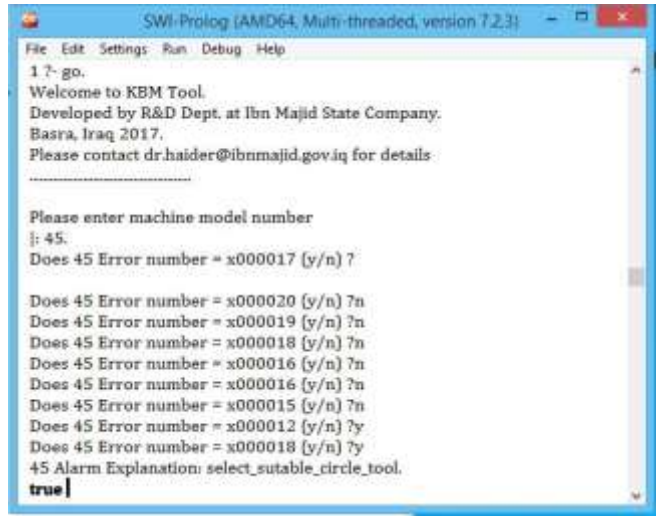

Figure 3 Implementation window of KBM tool.

Algorithm 1: KBM.

1: **Input:** θ_j , machine category

2: **Output:** alarm number, description message // fail or success

3: ***C*** ← set of all current rules (Initial-State [θ_j]) // ***C*** = all current rules

4: **while** (***C*** is not empty) **loop**

5: find a rule in KBS based on ***C***

//if there are several such rules in KBS, prefer a goal rule

6: R ← Get a rule from ***C*** // R= result

7: D ← Retrieve related data from KBS // D= description of failure

8: Insert R & D in **Output**

9: return **Output**

10: **end loop**

1) Formalization of the data gained to be distinguished. This data includes not only the clarified details related to a specific machine but also contains information to cover mechanical and electric concepts, software bugs, memory management errors and data communication protocol problems.
2) Optimal data matching. We designed a smart data matching algorithm through adopting software engineering steps in order to fulfill a useful and successful retrieve process of KBS contents.
3) Generation of maintenance reports. For the purpose of assuring that the gained information would be useful, KBMS generates an effective report for the end-users for diagnosing the machine fault and also recommend repair strategies.

7.2 Time Complexity Analysis

Now the time complexity of the KBM algorithm is analyzed. As indicated in the KBM algorithm, given the number of current rules *C*, there are two steps: set all current rules and find a goal rule. In the set of all current rules, the algorithm takes $O(\theta_j)$ to allocate time slots to all alarms. In the second step involving allocation of a goal rule, the algorithm loops θ_j times,

and in each loop, it runs at most C times for finding the goal rule. The running time of this step is $O(C)$. Consequently, the running time of the KBM algorithm is $O(\theta_j.C)$.

8. CONCLUSION

In this paper, a framework is introduced for repairing faults that occur too often in industrial machinery. Meanwhile, an optimal AI-based tool is proposed that aims at accurate values to retrieve information from KBS associated, afterwards it describes the alarms to diagnose the failure on the machine. To evaluate the performance of the KBM scheme, we measure and monitor five different machine parameters acquired from the machine to diagnose fault or to warn of an expected fault. Also, an investigation is performed on the effects of KBS contents on the probability of success for each maintenance process. The results showed that AI-based maintenance significantly enhances the accuracy and performance with respect to data matching approach.

DECLARATIONS

We wish to draw the attention of the Editor to the following facts which may be considered as.

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

We confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed. We further confirm that

the order of authors listed in the manuscript has been approved by all of us.

We understand that the Corresponding Author is the sole contact for the Editorial process (including

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