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Proposition of the methodology for Data Acquisition, Analysis and Visualization in support of Industry 4.0

Syed Imran Shafiq[a*], Edward Szczerbicki[b] & Cesar Sanin[c]

[a] *Faculty of Engineering and Technology, Aligarh Muslim University, Aligarh-202002, India*
[b] *Gdansk University of Technology, Gdansk, Poland*
[a] *The University of Newcastle, University Drive, Callaghan, 2308, NSW, Australia*

Abstract

Industry 4.0 offers a comprehensive, interlinked, and holistic approach to manufacturing. It connects physical with digital and allows for better collaboration and access across departments, partners, vendors, product, and people. Consequently, it involves complex designing of highly specialized state of the art technologies. Thus, companies face formidable challenges in the adoption of these new technologies. In this paper, critical components of Industry 4.0, their significance and challenges as identified in the literature are presented. Furthermore, a test case framework for the implementation of Industry 4.0 is proposed. The system covers four layers: decision support, data processing, data acquisition and transmission and sensors. Condition monitoring data from machines and shop floor are captured, stored, organized and visualized in real time. Knowledge representation technique of SOEKS/DDNA is used for doing the semantic analysis of the data, Virtual Engineering Object (VEO), Virtual Engineering Process (VEP) and Virtual Engineering Factory (VEF) are used for creating virtual engineering objects, process and factory respectively, Python and its utility Bokeh is used for visualization. The proposed Industry 4.0 framework will make it possible to gather and analyze data across machines, processes and resources supporting faster, flexible, and more efficient control and production of higher-quality goods at reduced costs.

Keywords: SOEKS, DDNA, Data Visualization, Industry 4.0

* Corresponding author. Tel.: +918755286666
E-mail address: SyedImran.Shafiq@uon.edu.au

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1. Introduction to Industry 4.0

Industrie 4.0 is also called Industry 4.0 which implies the beginning of the Fourth Industrial Revolution [1, 2] was initially introduced in 2011 in Germany. The first three industrial revolutions took around two centuries, and are the result of, firstly, the introduction of water and steam-powered mechanical manufacturing facilities; secondly, the application of electrically-powered mass production technologies through the division of labour; and thirdly, the use of electronics and information technology (IT) to support further automation of manufacturing [3]. The concept of the latest technological revolution, which is based on the concepts and technologies that include the Internet of things (IoT), the Internet of services (IoS) and cyber-physical systems (CPS) [4], based on communication via Internet that allows a continuous interaction and exchange of information not only between humans (C2C) and human and machine (C2M) but also between the machines themselves (M2M)[5].

Moreover, the idea of Industry 4.0 allows mass customization at a lower cost, higher quality, and faster processing. It is a vision where smart products, smart equipment and resources interact autonomously for dynamic optimization. However, for most enterprises, the methodology to adapt and implement Industry 4.0 is not transparent. In this article, a generic Industry 4.0 framework is explained for testing out new technologies and creating a new approach to production.

The structure of this paper is as follows in section 2, critical components of Industry 4.0 as identified in the literature and their significance and implementation challenges are outlined. Section 3 presents a framework for the implementation of industry 4.0. A case study is presented in section 4 in which whole body vibrations (WBV) and Hand Arm Vibration (HAV) coming out of a machine are monitored and analyzed in real time. In section 5, results of virtualization and visualization are shown. In the final section, the conclusions drawn from this research are discussed.

2. Critical Components of Industry 4.0

Industry 4.0 represents the automation technologies in the manufacturing industry, and it mainly includes enabling technologies such as the cyber-physical systems (CPS), Internet of Things (IoT) and cloud computing[6, 7]. According to German Trade and Invest (GTAI) (2014), Industry 4.0 represents the technological evolution from embedded systems to cyber-physical systems. Industry 4.0 is a research area of keen interest for industry and the academic world. Many experiments for the application of Industry 4.0 are carried out in a wide range of areas like Health care and social applications, Smart cities, Power System, Children keeper service, water distribution systems, Fire handling, Autonomous vehicle, Health Care, Communication and transportation [8].

In Industry 4.0, embedded systems, semantic machine-to-machine communication, IoT and CPS technologies are integrating the virtual space with the physical world; also, a new generation of industrial systems, such as smart factories, is emerging to deal with the complexity of production in the cyber-physical environment [9]. To achieve the functionality mentioned above, Industry 4.0 involves highly specialized areas of technology, the critical factors and the subfactors of these areas identified in the literature[10] are presented in table 1:

Table 1. Critical Factors and Sub Factors of Industry 4.0 and their significance

Factors	Sub Factors	Description
IoT, IoS and related technologies	RFID, Sensors, Actuators, GPS, etc.	IoT utilizes artificial intelligence techniques to create smart things or smart objects. Smart devices are capable of integrating tools, organizations, and information systems for data sharing and exchange; real-time monitoring; and using anything, anywhere, anytime communication to sense, capture, measure and transfer data [11-13].
	Connectivity and Networks, WSN, M2M	
	Data Exchange	
	People and Services	
CPS and CPPS	Integration of computational algorithm and physical components	CPS is the core foundation of Industry 4.0; it presents a higher level of integration and coordination between physical and computational elements [14, 15].
	Smart and Connected Communities (S&CC)	
	Virtual Objects	

Big Data and Analytics	Volume Veracity Variety Velocity Validity Volatility Cloud Computing Visualization	Data is often referred to as the raw material of the digital revolution. With a vast number of things connected to the Internet, a massive amount of real-time data will be automatically produced by connected things [16]. Unprocessed data may not provide meaningful value to decision-making in a cyber-physical production network unless these data are adequately analyzed and utilized for manufacturing decisions [17].
Cyber Security	Application Security Information Security Network Security Disaster Recovery/Continuity Planning Operational Security End User Security	A responsive, agile network is made possible only by open data sharing from all participants in the manufacturing network, which creates a significant hurdle; it will likely be challenging to strike a balance between allowing transparency for data and maintaining security. Organizations may thus want to consider ways to secure that information to prevent unauthorized users from accessing it across the network. They would also likely need to remain disciplined about maintaining those safeguards across all supporting processes[18].
System Integration	Horizontal Integration Vertical Integration End-to-end Integration	Vertical flow refers to company activities development and execution, including essential elements such as the organizational structure, human factor, departments relationships, technological and management level. In a complementary way, the horizontal flow includes external relations, establishes supplier and customer networks integration, information and management systems and others [19].
Others	Augmented reality Autonomous Robots Additive Manufacturing Simulation Standardization	An Industry 4.0 manufacturing environment is intelligent which requires more advanced technologies such as Autonomous Robots, Augmented reality, Simulation and Additive manufacturing [11]. Industry 4.0 utilizes artificial intelligence techniques and IoT to create smart things or smart objects. Arsénio et al. (2014) [12] propose to create the Internet of Intelligent Things by bringing artificial intelligence into things and communication networks [13]. Researchers have projected that future IoT systems would have characteristics such as self-configuration, self-optimization, self-protection and self-healing [20]. Smart objects will become more intelligent context-aware with more significant memory, processing, and reasoning capabilities[13].

2.1 *Challenges of adopting Industry 4.0*

- In CPS, physical entities, their virtual models and software components are deeply intertwined, each operating on different spatial and temporal scales, and interacting with each other in a myriad of ways that change with context [8].
- To analyze massive amounts of data generated from both IoT applications and ICT systems, data science and data analytics techniques should be developed and employed. Building practical applications in which big data from a verity of heterogeneous sources are integrated can be a challenging task [8, 21].
- The small and medium enterprises have not fully transformed the manual operation and data collection to the auto-collecting methods due to limitations of connection ability of legacy machinery [22].
- Conventional machines still play a significant role in factories as they guarantee production quality and efficiency. However, their communication with the whole Industry 4.0 system is not optimized. Upgrading

these old machines is costly and time-consuming, and causes a risk of productivity loss due to incompatibility and downtime [23].

- Smart devices enable ubiquitous computing. However, there are significant challenges at various levels, for Smart devices to have the capability of integrating devices, organizations, and information systems for data sharing and exchange; real-time monitoring; and using anything, anywhere, anytime communication to sense, capture, measure and transfer data [10, 21].

Thus, from the literature review, it was observed that one of the most critical challenges that companies encounter in implanting Industry 4.0 is to synchronize the conventional and legacy machine that can be compatible with the digital environment. Secondly, a mechanism is needed to create virtual models for these machines, and finally, a methodology is required to visualize the data coming out tools, devices and machines to make effective decision making.

3. A framework to implement industry 4.0

The main focus of this work is to contribute to the Industry 4.0 concept by proposing a model that entails the rapid transfer of new knowledge into industrial processes and products. In our work, we focus on the development of knowledge-based models engineering objects and processes. The proposed conceptual framework is divided into four stages: Stage 1-Data Collection platform, Stage 2-Data preparation and healing, Stage3-Semantic Analysis and Stage 4 - Real-time visualization as shown in Fig. 1.

The proposed architecture for a digital factory can help to create horizontal integration a strategic level, enable vertical integration and networked design and provide end-to-end integration across the entire value chain of the business process level.

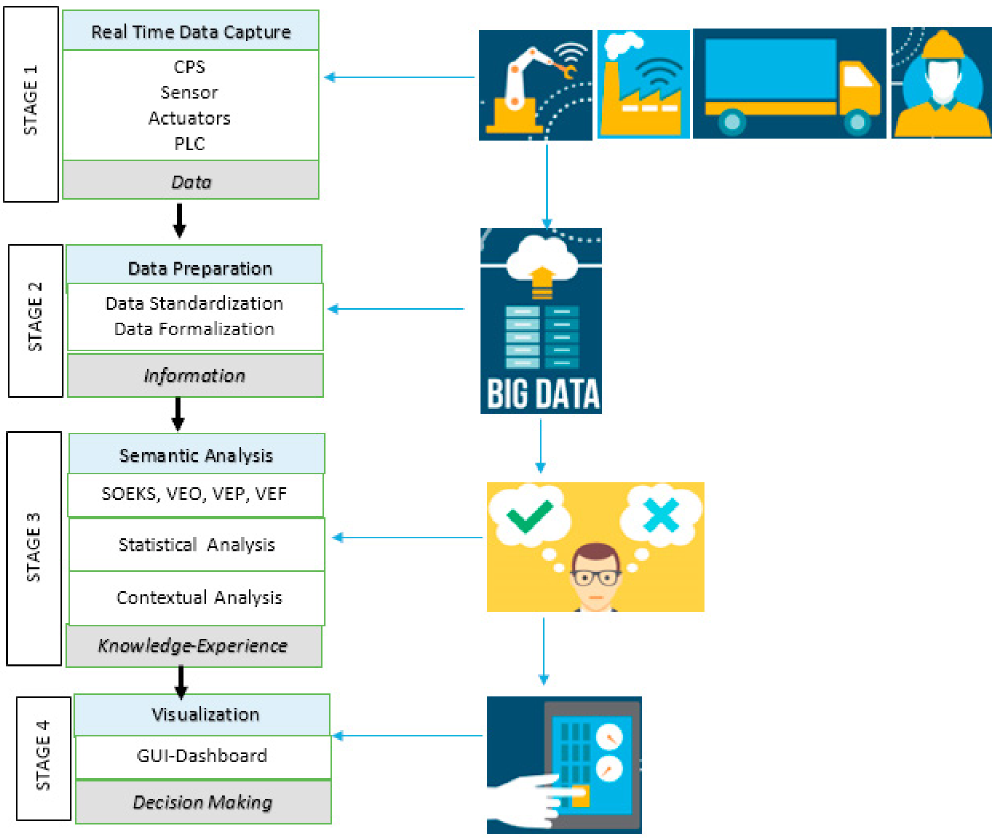


Fig. 1. Stages of the proposed framework

3.1 Stage 1-Data Collection Platform

In the proposed framework real-time data is collected through agents such as Sensors, RFID, Camera and Operator via a wireless network, for measuring product state, process and environment conditions.

3.2 Stage 2-Data preparation and healing

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

At the object level, data is arranged in a structured format of SOEKS to create VEO a specialized form of CPS. As an engineering process involves various process parameters along with many resources. Thus, at the process level information along with VEOs create VEP, a specialized form of Cyber-Physical Production System (CPPS)[22, 24]. At the next level VEF, which is an encapsulation of all the VEOs and VEPs is developed. Finally, the collection of VEOs, VEPs and VEF forms Factory Experience or Manufacturing DNA, through which exception information can be extracted [23].

The knowledge representation technique of Set of experience knowledge structure (SOEKS)-Decisional DNA (DDNA) [25, 26] is used for developing VEO and VEP models [27].

3.3 Stage 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 the previous section the semantic reasoner adopted is VEO, VEP and VEF.

3.3.1 Virtual Engineering Object (VEO) - Virtual Engineering Process (VEP) – Virtual Engineering Factory (VEF)

The concept of VEP and VEO can be assimilated with Industry 4.0 [24]. In a manufacturing environment, a collection of components/tools/objects constitutes a process. Following this pattern, the virtual representation of artifacts 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 artifact 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 a 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 critical feature related to an engineering object. It can be achieved by gathering information from following six different aspects of an object viz — characteristics, Functionality, Requirements, Connections, Present State and Experience [22, 23].

Virtual Engineering Process (VEP)

Virtual engineering process (VEP) is a knowledge representation of the manufacturing process/process-planning of artifact 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 areas mentioned above, the VEP is designed having the following three main elements or modules (i) Operations, (ii) Resources, and (iii) Experience.

Virtual Engineering Factory (VEF)

A VEF is a knowledge representation of a manufacturing factory by a collection of experience of integrated equipment and human resources, whose function is to perform one or more processing and assembly operations on a starting raw material, part, or set of parts. Different modules from which VEF gathers factory experience are (i) Loading/Unloading, (ii) Transportation, (iii) Storage, (iv) Quality Control, and (v) Experience[22].

3.4 Stage 4 - Real-time visualization.

Visual techniques are increasingly used for exploratory analysis and to quickly identify patterns in industrial processes. As Visual Analytics is 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 to build an interactive tool that can create customized visualizations. The user can visualize in real time different variables, graphs and charts, and compose its visualization configuration.

The visualization module is based on Bokeh, which is a Python interactive visualization library that targets modern web browsers. Its goal is to provide elegant, concise construction of novel graphics, but also deliver this capability with high-performance interactivity over very large or streaming datasets [28].

4. Case Study

4.1 Problem Statement

To develop a virtual manufacturing environment in which real-time data communication, monitoring, semantic analysis and visualization of KPI (like vibrations, noise, temperature, pressure, tool life) in real time over a network is done. The framework will be capable of facilitating effective decision making both at the planning stage as well as at the operations stage.

4.2 Methodology

A case study is designed specifically to capture vibrational data coming from machines, monitor it, analyze it and finally visualize it in real time. Whole Body Vibrations (WBV) and Hand-Arm Vibrations (HAV) data are collected from various sensors, measuring vibrations in X, Y and Z axis for Vibration analysis and diagnostic in accordance Australian Standard AS 2670.1-2001.

WBV measurements were conducted using a VI-400 Pro, hand-held real-time vibration analyzer from Quest Technologies as shown in Fig. 2(a). Vibration acceleration measurements were conducted in four axes simultaneously between the frequency range of 0.5 Hz to 80 Hz. Three of these axes were recorded using a seat pad sensor with the operator sitting on it (see figure 2(b)); transverse (X), longitudinal (Y) and vertical (Z).

HAV measurements were conducted using a tri-axial ICP accelerometer fixed to an H-shaped adaptor that fitted between the operator’s fingers and the handle of the machine tool being tested. Vibration acceleration measurements were conducted in three orthogonal directions using the frequency range between 5 and 1500 Hz. Third-octave vibration spectra were communicated using a proprietary occupational vibration analyzer.

Total number and type of these data sensors may vary according to different machining conditions. The purpose of choosing the sensors mentioned above 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 to support data capture coming from sensors recording vibration activities of the machines.
- Standardising data representation.

- Converting machine data stored in the database as SOEKS Structure.
- Using SOEKS to create VEO, VEP and VEF according to their format.
- Plotting streaming data in the client using visualization API based on BOKEH.

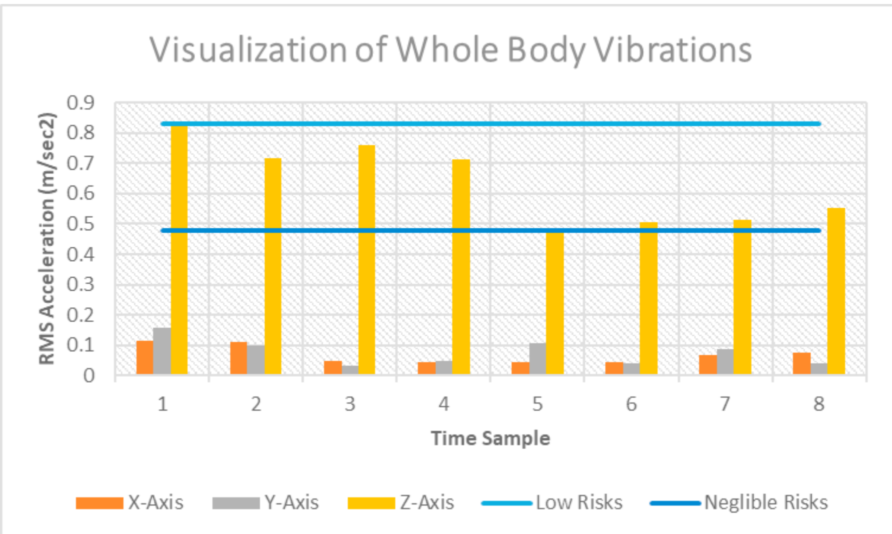
2(a) 2(b)

Fig. 2. Location of sensors capturing vibrations

5. Results

5.1 Data capture and visualization

As illustrated in Fig.3(a) and Fig. 3(b), information is continuously being pushed from machines. The principal role of the model is to manage the incoming data and to store the information efficiently. Storing streaming data is useful for the evaluation of machine performance and its maintenance. Any significant change to the status of the monitored machine can be detected. The change is defined as a dramatic variation (high and low as shown in Fig.3(a) and Fig. 3(b)) 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 current 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(a). Real-Time Data Visualization and Analysis of WBV in X, Y and Z directions.

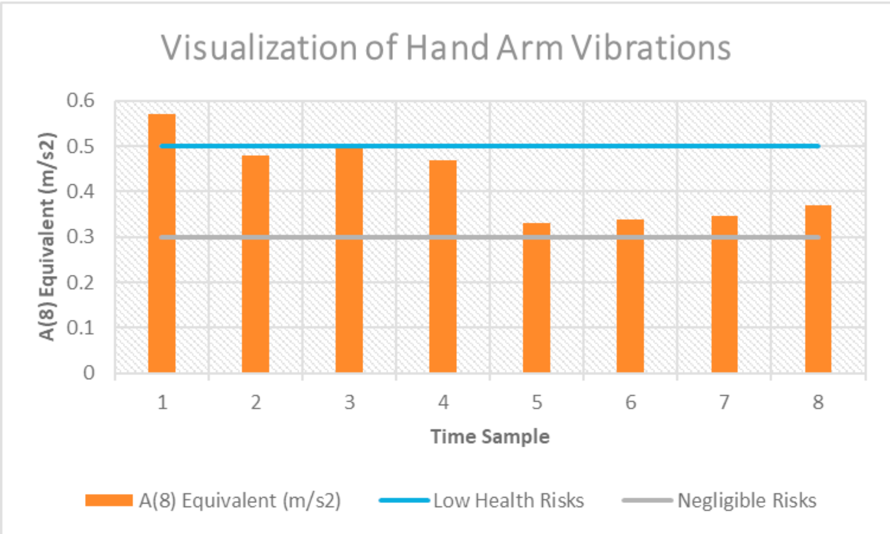


Fig. 3(b). Real-Time Data Visualization and Analysis of HAV

5.2 Performing semantics on the SOEKS similarity identification

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

Fig.4 shows the 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, the future behavior of the monitored system can be predicted more accurately.

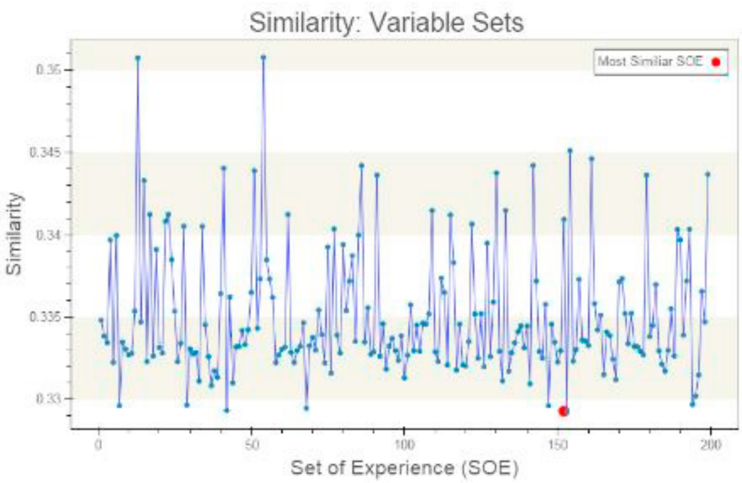


Fig. 4. Similarity identification for each SOEKS

6. Conclusion

In this article, firstly the concept of Industry 4.0 is explained; secondly, the critical factors of Industry 4.0 along with the subfactors and their significance are outlined. Moreover, the major challenges in the implementation of Industry 4.0 are identified. Thirdly, a general purpose Industry 4.0 framework is presented, which provides the mechanism right from the capture of data to its real-time visualization. Finally, a case study is presented based on the proposed framework, in which machine data is acquired, analyzed and visualized in real time. Moreover, Virtual copies of engineering objects, process, and factory in the form of VEO, VEP and VEP are developed.

Thus it can be concluded; if all the data from products, processes and factory are collected into a database, they can be searched, correlated and visualized with algorithms. Engineers can then discovery trends and patterns that reveal the "how" and "why" of decreases in the forecast. The quality team can pinpoint variances that require further investigation, identify where problems occur during a process. This approach has complete traceability right down to the specific parts and their serial number. The root cause of anomalies can be tracked down.

This work is an implementation of Industry 4.0 through a pilot initiative is limited to a single area, and IT systems support only a few processes. In the future, a full Industry 4.0 structure covering the entire product life cycle, flexible enough for adapting the dynamic industrial changes can be developed.

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