Department of Industrial Engineering & Maintenance

Procedures and techniques for improving the required function of systems

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Abstract: In today's industrial environment, enhancing the required function of systems is considered an important and crucial axis yet, a challenging aspect driven by the increasing demand for reliability, cost-effectiveness, sustainability, and market competitiveness across various sectors. To address this challenge, numerous techniques and procedures, ranging from traditional to advanced approaches have been developed, especially with the advancement of industry 4.0.
Techniques and procedures that aim to optimize and improve the required function of industrial systems have been identified in recent research articles. Techniques such as AI-based diagnosis and prognosis using Machine Learning including Deep Learning and neural networks supported by Internet of Things IoT, along with predictive maintenance and monitoring advanced methods, as well as Lean approaches such as Single-Minute Exchange of Die SMED and Total Productive Maintenance TPM have been implemented to improve the functions of industrial systems.
The main objective of this article is to synthesize the latest advances in maintenance procedures and techniques used to enhance the required function of industrial systems. It highlights the contribution and application of these different methods.

Key-Words : improving required function, artificial intelligence (AI), predictive maintenance, reliability, system efficiency, machine learning, real-time monitoring

Contents

1. Introduction

In the current landscape, improving the required function of systems is a significant challenge across industrial sectors, driven by the growing demand for reliability, cost-effectiveness, sustainability, and market demand. However, numerous techniques and procedures have emerged to address these challenges, including both traditional methods and advanced artificial intelligence tools. Their aim is to ensure that the systems perform effectively by optimizing and improving diagnosis, performance, reliability, and availability.

Technological evolution and innovation has influenced the field of improvement of the required function of systems in industries that seek to strengthen their performance, so they must continuously innovate to meet the increasing requirements for efficiency and availability of systems.

However, implementing these methodologies is subject to strict internal conditions, including production constraints, and at this time improving the required function of systems and equipment has become a priority and essential axis for industries because it allows them to achieve expected performance.

This article is based on an in-depth analysis of the literature in order to organize the different procedures and techniques that aim to optimize and develop the required function of systems. Among these techniques: AI-based techniques for diagnosis and pronosis, IoT-based monitoring and predictive maintenance, Lean Manufacturing approaches, and industry 4.0 technologies such as Digital Twins and IoT for data collection.

Furthermore, the human factor is a key element for the success and optimization of these systems, particularly in terms of training, commitment, and skill management.

The main objective of this research is to review the latest studies on improving the required function of industrial systems.

2. Research questions

The relevance of a review of the scientific literature depends essentially on the methodology used to select the appropriate publications. Due to the considerable volume of publications available in scientific databases, it becomes crucial to adopt a methodical and rigorous approach. To avoid dispersion and maintain targeted research, we have developed an analysis framework structured around three fundamental questions. These questions will serve as selection criteria to evaluate the relevance of each article to our study topic on the improvement of industrial systems:

- What are the main obstacles encountered in improving the required function in industrial systems?
- What are the main methodologies and tools used to optimize the required function of industrial systems?
- How does the human factor influence the success of actions to improve the required function of industrial systems?

This analysis grid will allow us to systematically identify and select the most relevant publications for our research, ensuring a solid basis for our study. The figure below represents the research questions of our study:

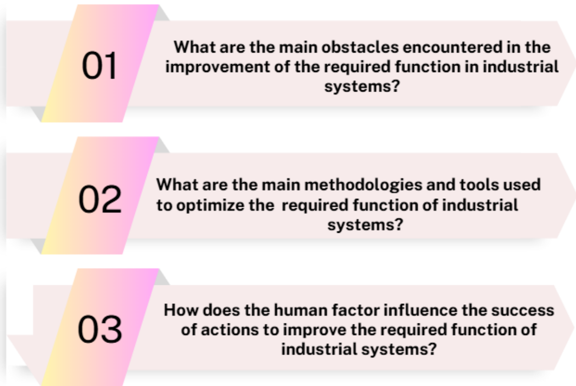

Figure 1: Research questions.

3. Research methodology

Our research is based on an organized and structured approach with the aim of establishing a global synthesis of techniques and procedures to improve the required function of industrial systems. This research was carried out in several main stages:

3.1. Selection of search engines and articles

The first step consists of the identification of the most appropriate search engines to collect relevant scientific and technical articles available on the SNDL platform. The research process mainly focused on a group of scientific search engines, which are the following: Google Scholar, IEEE, Science Direct, and other scientific search engines. In order to facilitate the search in these engines, keywords such as: "improvement of required function ", "AI and maintenance" were used. The next stage was the selection of recent and relevant articles related to the improvement of the function of industrial systems.

3.2. Literature analysis

After identifying the articles, an in-depth analysis of them was carried out in order to understand the concepts and results presented in the selected articles.

This step made it possible to identify current trends and the existing solution to improve the required function of industrial systems. The extracted data include the methods used, case studies, and practical results.

3.3. Construction of the synthesis matrix

The third step in our research approach consists of developing a synthesis matrix in order to organize and compare the information from the articles.

3.4. Identification of the main themes

The previous step facilitated the selection and identification of the main themes that we will cover in our article, five main themes were defined:

- The integration of modern technologies (Artificial Intelligence, Internet of Things, Digital Twins).
- The influence of industry 4.0 on improving the required function of systems.
- Monitoring and maintenance techniques.
- Diagnosis and prognosis based on AI.
- Lean manufacturing approaches.
- The importance of the human factor in the process of improving the required function.

3.5. Research synthesis

After a good reading and analysis of the identified articles, the last step consists of synthesizing the main findings of research.

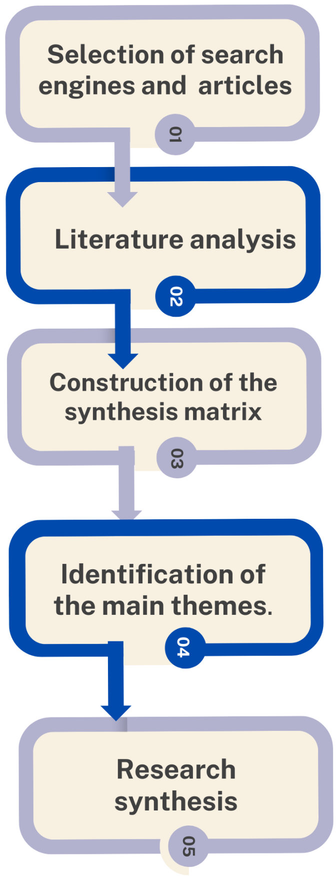

Figure 2: Research methodology.

4. Challenges and limitations in industrial system's function optimization

Improving the required function of industrial systems, although essential to improve productivity, efficiency, and performance, faces significant challenges[1].It is a complex task influenced by various factors, including system complexity, dynamic environment, and data issues.

4.1. Challenges due to industrial system's complexity increase

One of the most recurring obstacles is related to the increasing complexity of modern industrial systems, which integrate advanced technologies. These technologies, although effective, require a robust infrastructure and extensive technical expertise to be implemented effectively[2] and accurate diagnostics becomes challenging [3] and it is difficult to identify the alert rules[3] particularly, in critical sectors such as ammonia production[4]. This makes fault diagnosis based only on vibration signals challenging [5].
Traditional models that struggle to handle the growing diversity of systems[6], non- linearity[7], accuracy and

real-time responsiveness [8] and uncertainty of industrial processes[9]. This challenge, combined with harsh environment conditions, greatly affects reliability and safety [10], [8], and [9].

4.2. Challenges due to environmental conditions and traditional methods limitations

Industrial systems operate under complex conditions where the environment has a huge impact on their performance. Various researchers have highlighted these environmental conditions.
Traditional diagnostic methods based on the analysis of single signals are significantly limited due to the strong effect of noise[5].This challenge is intensified in complex working conditions such as for diesel engines, which are affected by high temperature, high pressure and a harsh environment[10].
In addition, traditional methods cannot capture deep features and potential trends in large-scale, multivariate, and industrial data with high noise that negatively affect the effectiveness of warning [8]. However, the advanced deep temporal clustering model with unsupervised data proposed by Hong and Dongjun for fault diagnosis proves robustness and offers high predictive accuracy in noisy environments over various time intervals [9].
Each system has its operating specifications and limitations[7], which is why there are no standards and rules for maintenance and repair that can be suitable for enterprises that have different environment conditions in which their systems operate[11]. In addition, the organizational aspect also poses significant challenges in improving required function. The introduction of new technologies and methods requires profound changes in corporate culture and the adoption of new practices. This transition is often confronted by resistance to change and lack of training of operators and managers [12].

4.3. Data challenges

The main issue traditional fault warning methods confront is the complex, high-dimensional industrial data. Industrial systems generate multidimensional variables including environmental factors that are difficult for a model that relies on statistical analysis to detect and predict faults in industrial systems to deal with and handle such complexity[8].
Traditional deep learning techniques even with their efficiency in many domains often leave out a crucial aspect which is the interdependency among data samples. This leads to under utilize structural information and geometric features inherent in the data [5]. As a result, the performance of applications where the spatial or temporal dependencies between data are essential is affected.
As for data-driven machine learning methods, the most significant challenge they deal with is the data sparsity of industrial systems. This problem is due to difficulties in data collection[9].

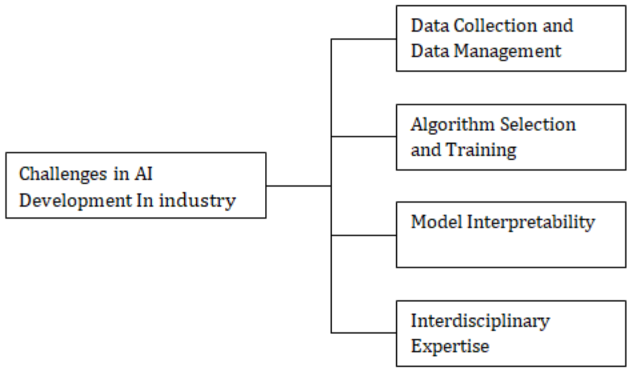

Figure 3: Challenges in development of AI application in industry [13].

5. Industry 4.0 technologies and techniques on improving the required function of systems

One of the main contributions of Industry 4.0 is the optimization of system performance through real-time data collection and analysis, where IoT sensors enable continuous monitoring of equipment, facilitating early detection of anomalies and the implementation of proactive maintenance strategies [2].

The digitalization of industry powered by the Internet of Things IoT and the widespread integration of sensors allows better knowledge of industrial systems and leads to high productivity through more efficient preventive maintenance [2], a technique consists of using IoT sensors linked to the line or objects connected to the operator for the visualization of data in real time, in order to warn of malfunctions [14]. According to [15], the IoT makes it possible to collect data in real time from industrial equipment. These data are used to monitor the state of the machines in order to detect and predict anomalies before they lead to critical failures, thus losing the required function. Industry 4.0 technologies also promote better connectivity and seamless integration of different components of industrial systems. These innovations help to to achieve better coordination between processes, which improves operational efficiency and reduces productivity losses [2].
This figure is the result of a scientific review conducted by a group of researchers emphasize that IoT and AI are the most researched and used technique in the pharmaceutical industry from 2019 to 2023[16].

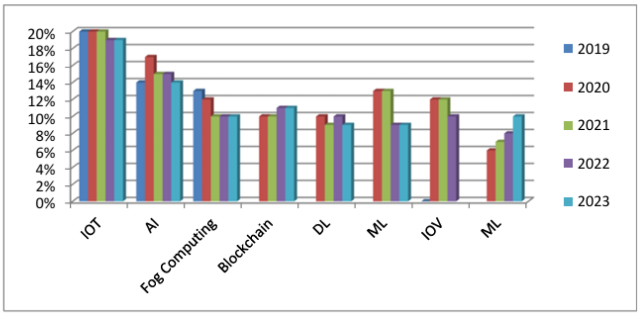

Figure 4: IoT and AI technologies application [16].

In addition, digital twins are a paradigm that plays a key role in improving the overall efficiency of equipment, thus improving the performance of production systems. The convergence of digital tools and methodologies such as Lean Manufacturing techniques creates unique opportunities to maximize the added value of systems while minimizing waste [12]. Thus, Industry 4.0 acts as a catalyst, not only to improve the required function of systems, but also to transform industrial processes towards a more intelligent, flexible, and resilient model. Studies show that companies that adopt these technologies strategically can achieve high levels of efficiency and competitiveness [17]. The following figure shows the Structure of Industry 4.0 elements:

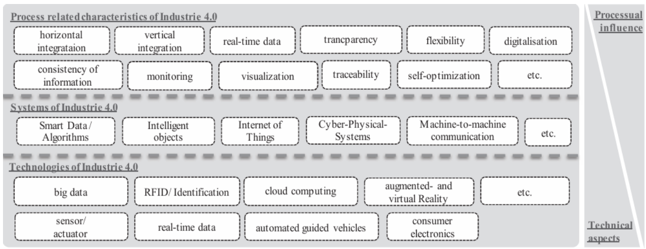

Figure 5: The structure of the elements of Industry 4.0 [18].

At the same time, the use of AI in processing these data offers advanced analysis capacity, making it possible to identify models that escape traditional techniques [19].

5.1. The contribution of digital twins in improving the required function of systems

The digital twin, an advanced industry 4.0 technology, optimizes overall equipment efficiency by anticipating breakdowns through predictive maintenance by detecting micro-failures [14]. Thus improving machine availability and reducing production losses. This solution aligns perfectly with the total productive maintenance (TPM) approach addressing the six main sources of efficiency losses[14].

It is a real-time virtual model that accurately replicates the physical, functional, and behavioral characteristics of systems, thus enabling continuous monitoring and optimization of industrial processes allowing early fault detection. Thanks to their ability to simulate the performance of equipment and systems, this technology provides a better understanding of operations and facilitate the proactive identification of malfunctions. For example, in a recent study [14], it was shown that the coupling of a digital twin with a neural network significantly improves the detection and analysis of micro-failures. This allows companies to intervene quickly to correct anomalies and thus avoid costly failures. Digital twins also allow testing different scenarios without disrupting real operations. This simulation capability helps optimize system configurations and assess the potential impacts of changes before they are implemented. Data from IoT sensors, combined with precise digital models, provides real-time visualization of systems, thus providing a competitive advantage in terms of flexibility and responsiveness[2]. In addition, digital twins play a key role in predictive maintenance. They integrate historical and real-time data to predict future failures and optimize maintenance strategies, extend the equipment's life, and improve decision making.

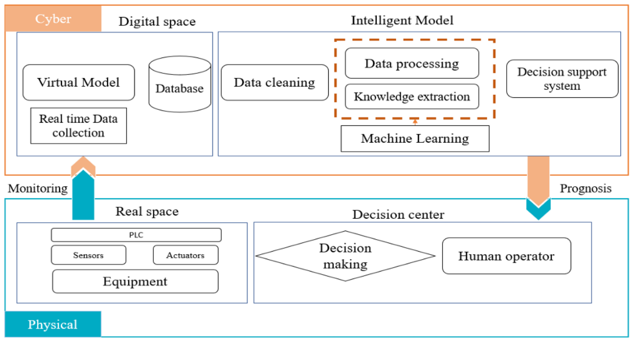

Figure 6: Decision making improvement system based on explainable artificial intelligence approaches applied to predictive maintenance [20].

The following figure shows a case study carried out by researchers [14] in the field of the use of digital twins systems improvement.

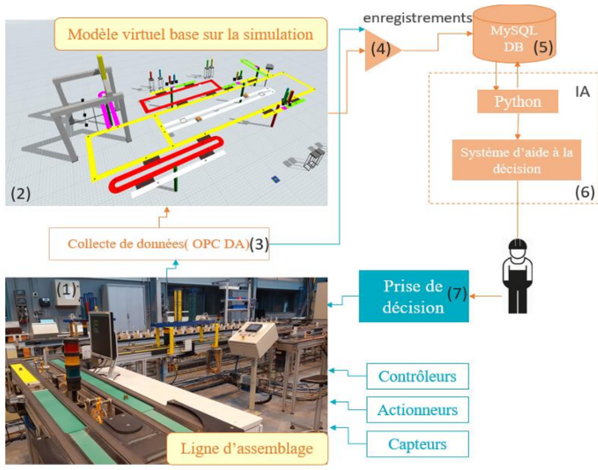

Figure 7: Implementation architecture of a cyber-physical system for predictive maintenance [14]

5.2. AI techniques in the improvement of system's function.

Machine learning methods have become an essential field of research in terms of improving the required function of systems. Those models prove their efficiency for fault warning, anomaly detection and predictive maintenance [21]. Among those techniques: deep learning methods,generalized neural network and data driven machine learning methods.

The integration of machine learning algorithms helps the prediction, optimization, and diagnostic operations of industrial processes in order to improve the overall efficiency of the industrial systems. It shows effective results in the field of fault warning and demonstrate high performance diagnosis[5],[8], and[21].

This innovative approach allows in particular a fine analysis of data to detect and classify anomalies in industrial processes [14].

It becomes widely used for diesel engine faults diagnosis due to its end to end nature and its ability to handle large amount of data even they have different structures and characteristics. Models such as Auto Encoder AE is used for extracting features, generating data. Recurrent Neural Networks RNN model acts efficiently when processing time-series data and for the Generative Adversarial Networks GAN model have its unique role with semi-supervised, unsupervised generative tasks [10].

Every model has its specifications, advantages and limitations:[10].

An illustration of the specifications and basic units are attached on AppendixB

1. CNN: Convolutional Neural Networks
    - It manipulates data with grid-like topology
    - Weight sharing, supervised learning.
    - Strong feature extraction capability and few parameters.
    - Limits: complex structure and large amount of data required.
    - Stacked multiple restricted Boltzmann machine layers
2. DBN: Deep Belief Network
    - It uses layer-by-layer greedy learning training model
    - Pre-training is unsupervised and supervised fine-tuning model.
    - Greedy training approach
    - Easy handling
    - As a disadvantage, it consumes a lot of time
3. RNN: Recurrent Neural Network
    - Includes feedback loops to preserve information
    - Suitable for time series processing.
    - Variable input length
    - As a limit,it is susceptible to gradient loss or explosion issues leading to instability in the model's learning process
    - It consumes a lot of time

    Here an illustration explaining the process of time series prediction for anomaly detection:

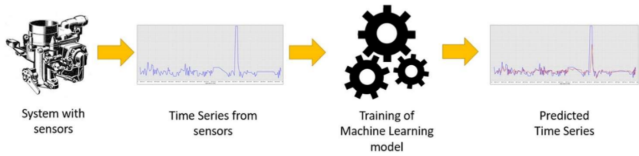

Figure 8: Process of condition monitoring [3].

4. GAN: generative adversarial Network
    - The generator component learns the input distribution and creates fake data; while the discriminator accepts both real and fake data and identifies the data authenticity. Consists of an encoder and decoder; reconfigurable input data; unsupervised learning
    - It doesn't need deterministic bias, generative model or Markov chain.
    - Variable input length
    - As a limit,it is unstable training.
5. AE: Auto Encoder
    - It is made up of an encoder and decoder;
    - it is an unsupervised learning model
    - suitable for noisy environment
    - it requires a pre-training is and the training may cause a gradient explosion.
6. CN: Cellular Network
    - It tackles some limitations of CNNs.
    - capsules represents features of a particular entity.
    - It can save information such as posture and position of features
    - As a limitation, it requires a large amount of calculation.

The Generalized Regression Neural Network (GRNN) is one of the most machine learning used model due to its simplicity, effectiveness, and applicability to various fault warning scenarios.

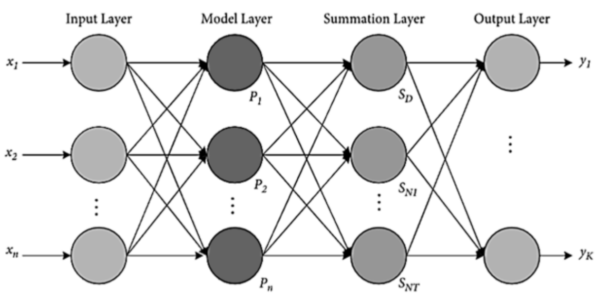

Figure 9: The GRNN model structure [22]

The model is composed of four layers: the input layer processes the feature vectors of input samples, while the pattern layer store the training samples' feature vectors with their associated output values. The weights then are calculated in the pattern layer by assessing the similarity between the input sample and the stored ones, then performs a weighted summation of the output

values that are used by the output layer as the final prediction output [22].
The authors start from this generalized neural network model to propose there hybrid method the ESCSO (enhanced sand cat swarm optimization) to avoid problems due to the local Optima. their model is based on the SCSO algorithm (sand cat swarm optimization) witch is a meta-heuristic algorithm used for complex optimization problems[22] (AppendixA).
The ESCSO algorithm shows a great success according to the experiences carried by these researchers. there results are shown in this figure:

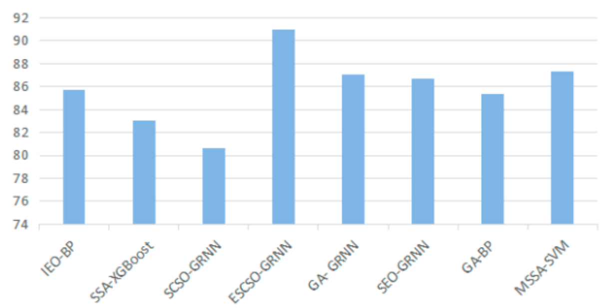

Figure 10: Comparative results between ESCSO and other algorithms [22].

Another group of researchers developed an augmented mel spectrogram image-based learning data to deal with the data sparsity issue and data imbalance problems found in industry and machine learning-based methods.

6. Monitoring and maintenance techniques and strategies

Effective monitoring techniques and maintenance strategies are essential to for improving overall equipment efficiency, reliability and maintaining useful life.

6.1. The impact of predictive maintenance in improving required function

Anomaly detection plays an important role in maintaining efficiency[3] and useful life[23] in predictive maintenance where finding anomalies in early stages is important for performing maintenance activity to avoid unplanned breakdown, improving reliability and availability. [24]. This proactive approach is based on the analysis of data collected by intelligent sensors, allowing to detect anomalies and predict potential failures before they occur[21].
A monitoring condition which is a statistical process control is carried to monitor quality in manufacturing domain [3].

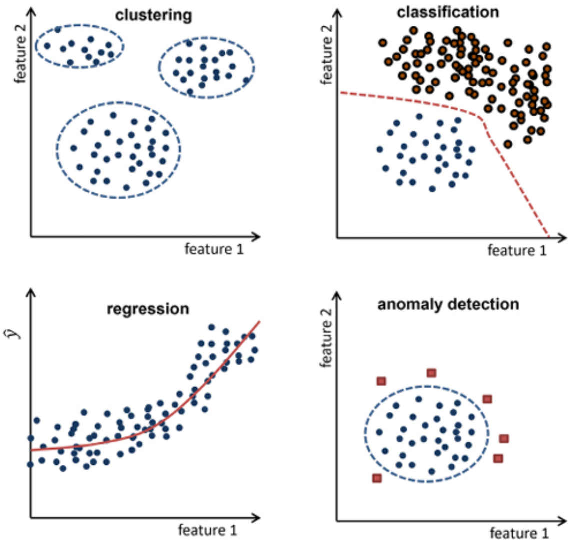

Figure 11: Machine learning tasks most relevant for predictive maintenance[25].

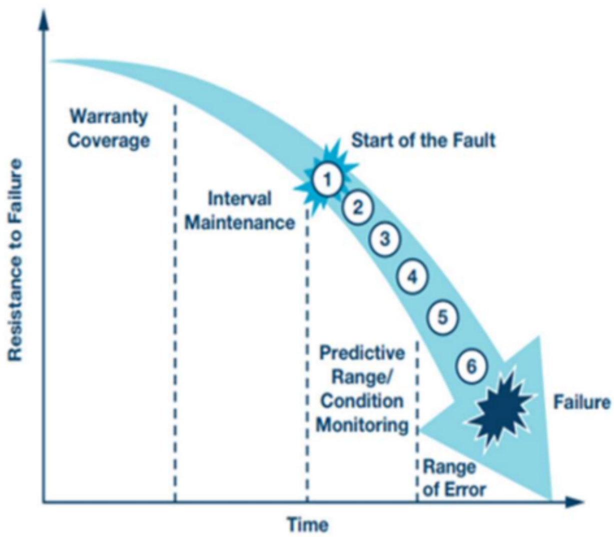

Figure 12: Process of condition monitoring [3].

Introducing technical diagnosis methods is essential to periodically monitor and control equipment parameters increases the reliability and optimize repairs[11], [26],[27]. Advanced technologies are integrated to continuously monitor in real-time the industrial equipments, thus providing unprecedented visibility into their health status.
Many techniques have been developed to support predictive maintenance strategies, root cause and fault detection and repair. A group of researchers propose a CVC-Net (convergent viewable graph neural network). It is based on the correlation-variance contribution algorithm, a model designed to reduce mapping time and enhance efficiency in diagnostic precision and reliability in complex environments[5]. Other have developed a new approach using machine learning to design a decision support tool. This method,

based on predictive maintenance and powered by IoT data, in order to monitor the health of industrial systems, including wind turbines, and improve their performance[20].

6.2. AI-based diagnosis and prognosis health management for system improvement

Early detection, isolation and identification of failures will help to significantly improve the efficiency, reliability and repeatability of industrial systems [19],[21]. Reliability issues have gradually become the key of whether many modern industrial systems can be truly practical. Once a failure occurs, it may affect the safe and stable operation of the entire system. Therefore, the early identification of faults in advance can greatly help to take appropriate actions of maintenance to avoid the undesired consequences (loosing the required function and endanger personal safety) [19].
An other field of research is the Prognostic Health Management technology (PHM) to improve equipment reliability and safety. When diagnosis identifies the causes of current anomalies, prognostic focuses on predicting future failures and the remaining useful life of equipment[19]. It is composed of seven main layers, for diesel engine for instance[10]:

1. Data acquisition layer:
   - Data reflecting the operation state of equipment are collected by an acquisition system
   - A data transmission system transmit the data to the next layer
2. Data processing layer:
   - reduce signal noise by filtering, deconvolution, deep learning methods...
   - extract signal features(Signal demodulation analysis,signal decomposition algorithms, entropy representation, time-frequency characterization and graph signal processing
   - reduce features dimension(Unsupervised discriminant projection...)
3. Fault diagnosis layer:
   - analyzing the fault warning
   - locate faults
   - use diagnosis methods such as knowledge-based approach,model-based approach, signal processing-based approach and data driven model-based approach)
4. Health assessment layer:
   - identify the degradation status of the diesel engine
   - classify the status of the engine health
   - methods such as knowledge-driven approach, model-driven approach and data-driven approach are used in this layer.
5. Life prediction layer:
   - Analyze the remaining life prediction diagram
   - methods such as physical model, data-driven model and mathematical model are used to determine the remaining life.

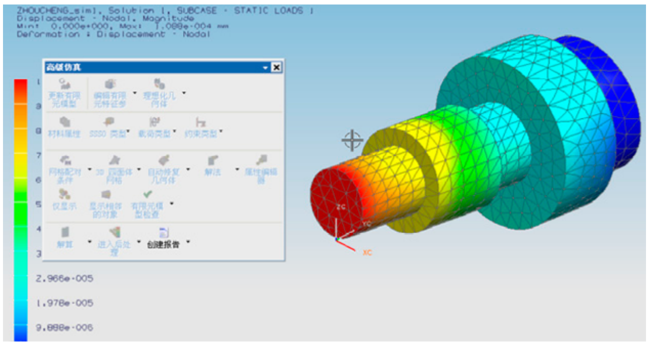

Figure 13: Physical model [10]

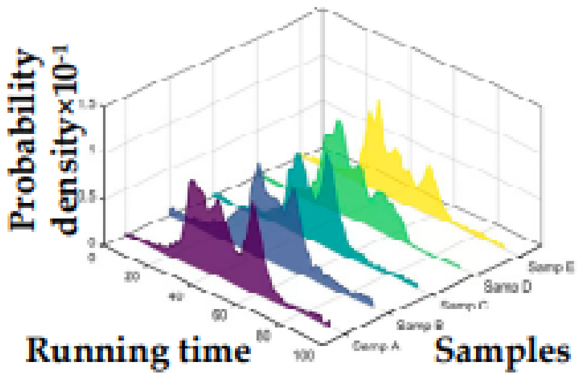

Figure 14: Mathematical model [10]

6. Decision support layer:
   - using maintenance supports as input (history task profiles mission objectives, resource constraints, data from life-prediction layer and health assessment layer.
   - making decision about the timing, type and level of maintenance tasks.
   - The models and technologies used are cost-based maintenance decision model, availability-based maintenance decision model, risk-based maintenance decision model.
7. Decision making advice layer:
   - storing data and management
   - big data analyzing
   - consultation Report

The concept of artificial intelligence is exploited in the field of diagnosis and prognosis due to the ability of AI systems to analyze a large volume of data, therefore they allow to obtain reliable data in real time thanks to machine learning algorithms [2]. For this, implementing IoT is considered as the most efficient solution addressing real-time monitoring[4], [3].

6.3. Software tools in Maintenance

Automation and software computing has become an indicator of effective maintenance, this enable industries to reduce manual intervention and maximize the precision of reliability estimation.
Automated software tools play an essential role in enhancing repair tasks and introducing advanced diagnostic capabilities. These tools minimize human error and improve precision of reliability estimation [6]. These software can automate activities such as forecasting, monitoring ,control and management of energy facilities [7], those are essential functions that maintenance has to manage in order to improve the reliability of equipments.
Due to its advantages, SKF; a mechanical industry company, proposes installing an online system for condition monitoring in order to support customer collecting abnormality conditions [23].

6.4. The impact of limited maintenance strategies

A limited maintenance strategies have a significant impact on equipment reliability and operational performance. It can lead to production waste and increased costs in industrial operations and loose the required function as well.
In fact, poorly planned maintenance causes operational inefficiencies and lower productivity by reducing the equipment's overall productive capacity (The reduction by five to twenty percent[3]). Therefore, the implementation of an automated maintenance system can be an appropriate solution to reduce inefficiencies and enhance overall performance[11]. The AppendixC shows the maintenance standards adopted in metal forming industry.

7. The application of the Lean manufacturing approach in the improvement of systems.

Lean manufacturing is an approach that aims to avoid waste [12] and to improve companies and industrial systems [2],[18]. Techniques of Lean Maintenance especially are used in order to detect the root causes of inefficiency[28] The wastes in terms of maintenance function are mainly: over maintenance, poor organization of spare parts warehouse(overstock or out of stock), maintainability problems (higher Mean Time to Repair MTTR),poor maintenance organization and absence of maintenance procedures standards[28].
The general structure of Lean Production Systems is set up with a composition of the elements objectives, processes, principles, methods and tools, while the content of these elements is company-specific. Figure 2 gives an overview of the five main levels, building the organizational structure of a LPS[17]. This approach has proven its effectiveness in various industrial sectors, particularly by strengthening the required function of systems.
Lean manufacturing approach becomes more effective when combined with advanced Industry 4.0 tools [29] [17]. This allows the production system to be flexible, meaning that it can be configured to adapt to new circumstances in a short time [12].
Lean techniques combined with Fuzzy techniques and mathematical techniques provide a structured framework for decision-making, enabling industries to predict potential issues and solve them proactively[28] Combining these approaches, industries can achieve high precision and productivity, cost-effectiveness, waste elimination.

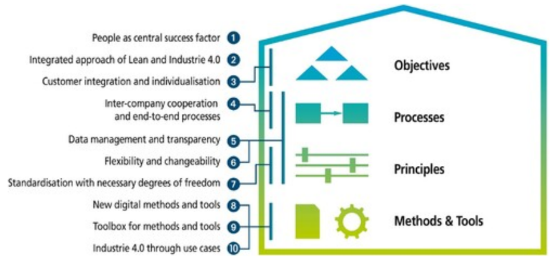

Figure 15: Organizational structure of Lean Production Systems[17]

7.1. Total Productive Maintenance (TPM) in systems improvement.

Total Productive Maintenance is one of the five essential principles of Lean Maintenance and can be defined as a strategy that applies to the management of maintenance processes, aiming to obtain the maximum efficiency of a production system. TPM has now become a global approach to industrial excellence focused on equipment to optimize manufacturing productivity. In addition, it contributes to the optimization of predictive, preventive and corrective maintenance and allows companies to achieve an optimal level of operational performance [2].
The total productive maintenance prove high efficiency in several domains. In the field of metal forming industry, TPM improves the total equipment efficacy of all workstations including rolling, bending, cutting, and die punching. It had a huge impact on the set-up time, where it has been decreased for workstations according to researchers[30].
There are principally six losses that limit instrumentation effectiveness noted by the researcher. These are failure (breakdown), setup and adjustment period of time, idleness and minor stoppages, reduced speed, method defects [31]. Thus, enhancing the efficiency and ensuring that the system meets its required function[32] by emphasizing preventive maintenance and the involvement of all employees [32].
In fact, it requires full commitment from the top management[30] to ensure that tasks are

effectively managed and coordinated between various departments[30]. Since TPM impacts the entire organizational structure, it is important to establish strong collaboration and communication among all departments[30]. As for the implementation of TPM method in the Nigerian industry by giving great importance to staff training [33] .

Thanks to its eight fundamental pillars, including autonomous and planned maintenance, TPM helps reduce unplanned breakdowns, optimize equipment efficiency and increase their service life.

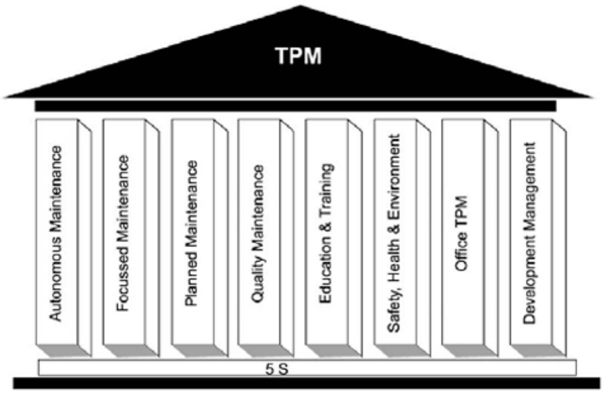

Figure 16: The pillars of the TPM approach [32].

A concrete example of the importance of this approach is cited in [33], the researchers deployed the TPM concept in a cellular manufacturing company. They found an availability rate of 62 percent and concluded that a sustained implementation of TPM is necessary to achieve an availability rate greater than 85 percent.

7.2. SMED in systems improvement.

SMED (Single-Minute Exchange of Dies) method is another Lean method that is considered as an effective technique for minimizing changeover times and boosting productivity. It is a useful approach for maintenance tasks, it can enhance maintainability and availability of equipments, thus aligning with the objective of achieving sustainable industrial operations and production process quality[28]. In maintenance, this approach allows minimizing downtime during equipment transitions,eliminating unnecessary tasks during interventions for more flexible and efficient operations.

8. The importance of the human factor in system optimization

The evolution of technologies and Industry 4.0 applications redefine operational processes. For many companies, this transformation remains a "black box" and new management approaches are needed to successfully overcome future production challenges[34]. Despite these significant technological advances, the human factor is a key element in improving the required function of industrial systems. The role of maintenance professionals and operators' participation in effective communication is crucial to ensure the reliability and efficiency of industrial systems, in general, and the achievement of the goals of every Lean approach. Integrating a human factors approach at the industrial system level helps strengthen the reliability and overall performance of these systems [35]. Placing humans at the heart of the industrial system and in process safety reaches higher levels.

In addition, it is clear that the place of humans and the organization in industrial systems remains crucial to achieve better performance. To meet the challenges facing industrial systems, this element must be continuously developed through training, support, planning, and efficient management.

Maintenance professionals often rely on manual methods to identify breakdowns and perform scheduled preventive maintenance, which can be time consuming and inefficient[10]. To overcome these challenges, industries need access to experts and advanced techniques to manage maintenance tasks effectively and develop sustainable and human centered systems[34]. Without the right conditions, tools, and parameters, organizations risk operational failures that could impact their overall performance and sustainability [30].

Furthermore, such an approach centers perspectives for future research on the human factor in the design and management of production systems, as well as the development of decision support systems. Operators should play an active role in decision-making processes and experience return, particularly in assessing equipment deterioration, as their involvement is key to evaluating and addressing issues since they are always near machines[30]. That can help overcome challenges such as digital transformation and contribute to the achievement of long-term sustainable business processes[34].

9. Discussion of the results

Our study highlights several techniques and procedures for improving the required function of systems where a successful implementation relies on a balanced combination of technology and human factor.

Impact of Industry 4.0: The results demonstrate that the integration of Industry 4.0 technologies fundamentally transforms the approaches to improve system's function, in particular by:

- The ability to collect and analyze data in real time.
- Improving data-driven decision making.

Complementarity of approaches: The results show that an integrated approach, combining advanced technologies (Industry 4.0) and traditional methodologies (Lean Manufacturing), offers more effective results.

The importance of the human factor in this

improvement process: After the literature review, it was found that the human factor remains the determining element in the success of improvement projects despite technological development. Continuous training, operator participation and effective change management appear to be an important axis in the system improvement process.
Implementation challenges: Our study reveals that the improvement process faces several challenges such as resistance to change, lack of suitable skills as well as the challenges related to industrial environment complexity and data challenges.

10. conclusion

Our research has identified and analyzed the main and important axes related to the improvement of the required function of industrial systems. The in-depth literature review reveals that the strategic integration of advanced technologies such as the Internet of Things (IoT) and artificial intelligence (AI), combined with Lean approaches, serves as a powerful lever for industrial transformation. These technologies enable real-time monitoring of equipment, more precise predictive maintenance and continuous optimization of performance.
Our study particularly highlights the importance of digital twins, which offer new perspectives for the simulation and optimization of industrial systems and demonstrate the ability of deep learning and machine learning approaches to effectively handle complex data and enable better accuracy and efficiency in complex systems.
However, the integration of the human factor is an essential axis in this improvement process, and helps to ensure the success of these improvement initiatives. Continuous training, active involvement of operators and effective change management appear to be essential conditions for success.
Our research results demonstrate that the optimization of industrial systems can only be achieved by combining advanced technologies, effective maintenance strategies, and the development of human skills. This combination allows industrial companies to significantly improve the availability, reliability and performance of their systems.

11. Acknowledgments

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12. Appendix A

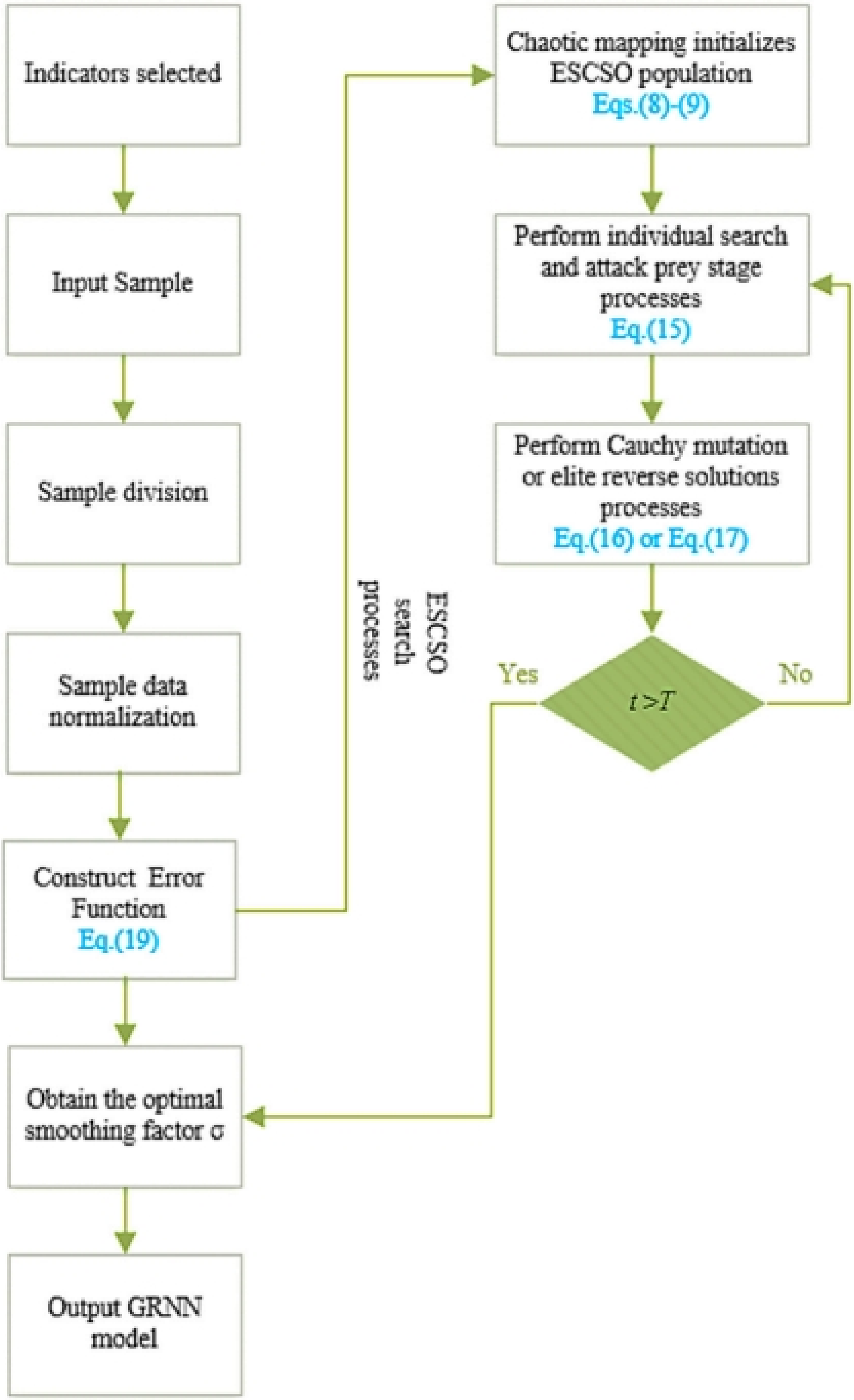

Figure 17: Enhanced SCSO model chart [22].

13. Appendix B

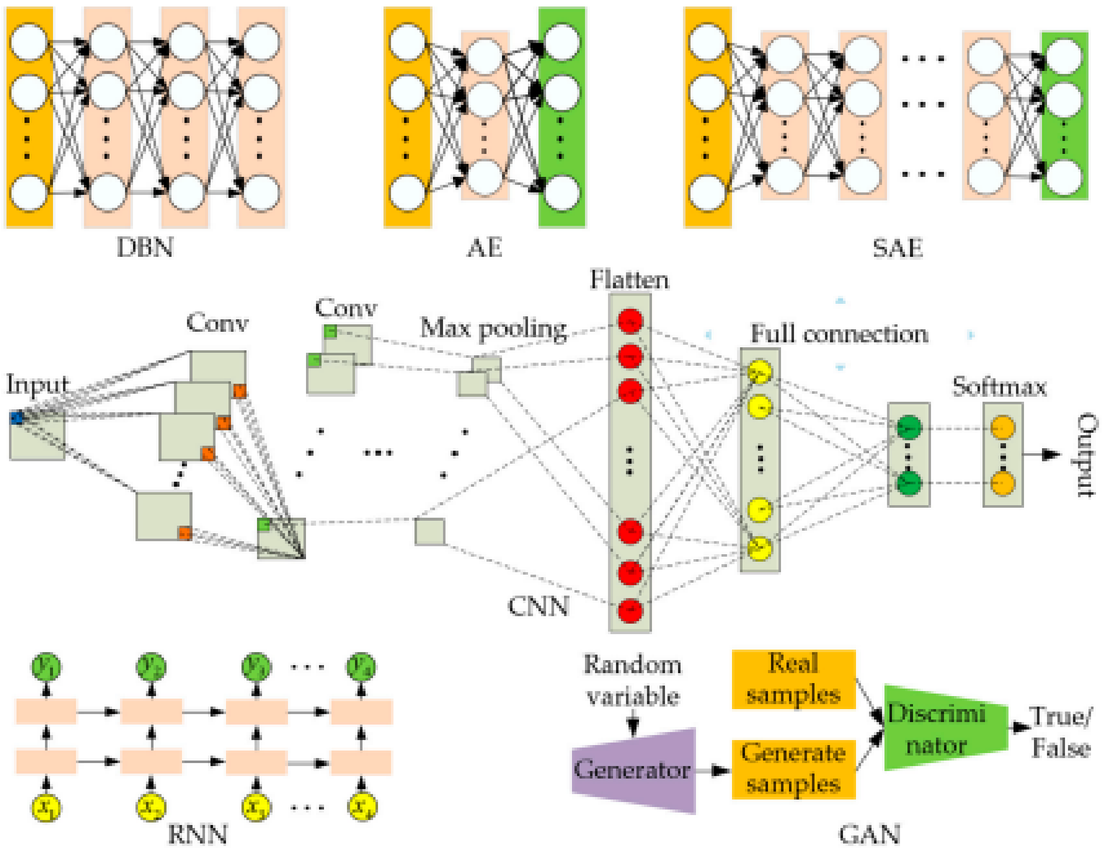

Figure 18: Basic units of typical deep learning models [10].

14. Appendix C

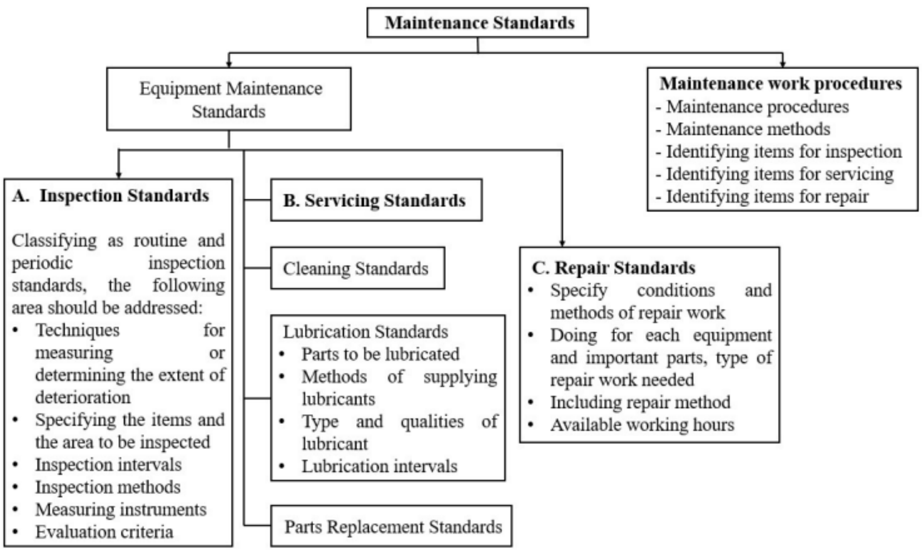

Figure 19: Maintenance standardization in metal forming industry [30].