International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING

ISSN:2147-6799 www.ijisae.org Original Research Paper

Optimizing Engineering Processes through Intelligent Systems and Automation

[1]Valluri Daneesha, [2]S. Balamuralitharan, [3]Santhoshkumar S., [4]Dr. Someshwar Siddi, [5]Ch Soloman Raju

Submitted: 05/02/2024 **Revised:** 25/03/2024 **Accepted:** 02/04/2024

Abstract— The emergence of intelligent systems and automation have transformed different industries especially the area of engineering. This paper investigates the possibilities of exploiting these technologies for optimizing the engineering processes. With the use of artificial intelligence (AI), machine learning (ML) tools, and automation tools, the engineering processes can be more efficient, precise, and flexible. This study seeks to analyse how intelligent systems and automation can be implemented to get better outputs in engineering in the design, manufacturing, and maintenance stages. The approach involves the thorough review of already-existing systems, along with practical application of case studies indicating use in reality. The results show major improvement in operating performance, decrease in errors and improvement of decision-making capabilities. Lastly, the paper outlines the challenges, the expected implications and the future of the intelligent systems in the engineering processes.

Keywords— *Intelligent Systems, Automation, Engineering Optimization, Artificial Intelligence, Machine Learning, Manufacturing Efficiency, Process Automation, Engineering Design, Smart Manufacturing.*

I. INTRODUCTION

As we may see recently, the engineering discipline has not only developed but has been transitioned rather substantially, primarily because of the smart systems and automation integration. Such enhancements have enabled some processes in such as design and manufacturing to be optimized; maintenance and operation management also. The embracement of artificial intelligence (AI), machine learning (ML), and automated systems did not only increase the output of the traditional engineering work, but it facilitated us to access radical solutions that were formerly impossible even to imagine [1-2].

Engineering processes no matter whether it be in a design phase, production phase, or a maintenance phase are all too frequently burdensome and resource deep. The traditional way of dealing with such processes was carried out through heavy manual intervention that was effective but with some degree of errors and inefficiency brought by delays caused by manual handling. The interaction of intelligent systems making the use of AI algorithms and data-driven decision-making in the process can contribute tremendously to speeding up, augmenting the accuracy and making the processes more flexible. On the other hand, automation reduces dependency on manual work, rules out human errors and ensures occurrence of the same on tasks that are physically extreme with a monotonous nature.

For an instance, in the manufacturing context, one may name the possibility of optimization of the schedules of production through the implementation of AI systems; prevent failures of the machines beforehand; even automatize quality control. On the same note, in the design of engineering area, generative design algorithms can propose new

[1]*Research Scholar, Department of Computer Science Engineering, Delhi Technological University, Shahbad Daulapur, Delhi - 110042*
daneesha.valluri@gmail.com
[2]*Adjunct Faculty, Department of Pure and Applied Mathematics, Saveetha School of Engineering, SIMATS, Chennai, Tamil Nadu, India*
Email Id: balamurali.maths@gmail.com
[3]*Assistant Professor, Department of Mathematics, Patrician College of Arts and Science, Chennai, India*
santhoshkumarsesa@gmail.com
[4]*Associate Professor , Department of FME, St. Martin's Engineering College, Dhulapally, Secunderabad-500100*
someshsiddi@gmail.com
[5]*Assistant Professor, Department of Computer Science & Engineering , Aditya University, Surampalem, India,*
solomanrajuch@aec.edu.in

optimized outcomes that meet functional and environmental demands. These systems not only save time in the usual engineering functions but rather provide the flexibility in accommodating changing markets' demand and tech revolution [5].

The benefits of intelligent systems and automation are not only limited to the manufacturing or design. In such industries such as construction, aerospace and automotive engineering, such technologies are having excellent effects. From project management to real time decision to day decision making all is optimized with such help as smart sensors, embedded systems and advance control mechanism. Real time collection, processing and analytics of large sets of data may bring into the fore new heights of efficiency, sustainability and innovation in many branches of engineering [13-15].

Notwithstanding the unlimited potential of the intelligent systems and automation in the engineering processes there are several challenges that need to be overcome. The high initial cost of applying these technologies may constitute a great barrier for small and medium-sized enterprises (SMEs). Also, there is building up of demands for upskilling and reskilling the workforce to make sure that the workers can cope with the new tools and systems that they are being subjected to. Additionally, there are ethical considerations that come with automation like job displacement and data privacy that must be well tended to circumvent possible societal effect.

The purpose of the present paper is to discuss the role of intelligent systems and automation in the engineering processes optimization. By taking a look at the existing literature and by providing examples of case-studies from different industries, we will see how these technologies have been implemented to increase efficiency, decrease costs, and, generally, enhance quality of the engineering procedures. The issues and obstacles to the implementation will also be discussed, including the possible mechanisms to eliminate them [4].

Novelty and Contribution

This paper adds to the existing body of knowledge insofar as it presents an all-round study of the application of intelligent systems and automation to optimize engineering processes. Whereas other research has concentrated on the applications of AI and automation on certain engineering fields, this paper takes a comprehensive look at the possible applications of the said technologies throughout the Engineering lifecycle [11].

One of the main contributions of this paper is the concept of intersection of AI, ML, and automation in engineering. Most research articles tend to focus on either of the above technologies alone. This paper, however, shows how the synergy of data-driven decision-making of AI, predictive powers of ML, and precision brought about by automation can result in synergistic enhancement of engineering processes. The holistic approach outlined in this piece provides a better understanding of the possible effects of the technologies when they are incorporated as part of the engineering workflows without any noticeable hiccups.

In addition to this, in this paper, there are shown real-world case studies that show the practical implementation of intelligent systems and automation. Through these case studies, learnings from the difficulties and achievements of implementing these technologies will be gained, which could be applied to implementing them in other fields of engineering in the future. By looking at the ways in which various industries have applied AI and automation, this paper helps to close the gap between theoretical studies and the practice.

The other important contribution is the discussion of the ethical and societal implications of automation in engineering. The further evolution of the automation makes its impact on the workforce and the society in general more important. This paper took a critical view of the possible challenges that would arise from automation, where the consequences may include job losses and issues of having data privacy and how best to address these challenges while exploiting the potential benefits of intelligent systems [10].

Lastly, the paper examines future studies and developments in the engineering optimization using intelligent systems and automation. We are in the midst of the quick adoption of technology, and there is a pressing need for a constant improvement in these spheres. The paper outlines the map for future studies of what will be emerging trends and what will remain as opportunities to explore.

To summarize, the novelty of this paper is in its thorough discussion of how the intelligent systems and automation may help to optimize engineering processes. Through an examination of the technologies and the applications of these systems, the paper presents useful insights to researchers, practitioners and policymakers interested in using these technologies in improving the performance of engineering [9].

II. Related Works

In 2020 W. Sha *et al.*, [6] introduced the last couple of years, integration of intelligent systems and automation into processes of engineering has become a popular area of research. Lots of works are devoted to the impact of these technologies on various stages of engineering, although the central sphere of interest is efficiency, accuracy and decision number improvement. Intelligent systems of artificial intelligence (AI) and machine learning (ML) can be very promising to replace human tasks carried out like design, test, and maintenance.

In the field of engineering design, the generative design algorithms and optimization tools have revolutionized how engineers resolve problems. Such systems use very complex algorithms to analyses various design alternatives and come up with viable solutions that will satisfy the imposed constraints in order to generate more efficient and more innovative designs. Moreover, the use of AI-based simulations has been popularized in the engineering processes, whereby designers can experiment and iterate designs virtually before their realizations of physical prototypes.

In 2023 V. P. S et.al., [12] suggested the automation of the manufacturing processes has resulted to significant gains in terms of operational efficiency. Robotic systems along with AI and ML algorithms are today heavily applied to automatize repetitive actions like assembly, welding, or quality control. Not only does these systems increase the speed of production, it also decreases the level of human error thus increasing consistency and precision. Besides, automation has promoted the use of the “smart factories” where machines can communicate with each other and adapt processes in real-time utilizing data analytics and achieving optimal workflow and downtime.

Another aspect where great improvements have been made with respect to predictive maintenance would be through the use of AI and ML. Historical data collected from the equipment’s sensors through the application of the machine learning algorithms can be used to predict when a machine is likely to fail thereby making it possible to do preemptive maintenance that prevents unplanned downtime. This is especially useful in such industries as the aerospace, automotive, and manufacturing where components’ breakdown may cause huge financial losses and risk to the life of production workers.

Although the benefits of intelligent systems and automation are obvious, there are several issues that remain. Its high cost of implementation, especially in SMEs is one of the major barriers. The price of purchasing sophisticated AI systems and their assimilation into existing workflows and training employees to use them may be unaffordable for many organizations. In addition, discussions about the privacy of data, cybersecurity, and elimination of jobs by automation are constantly raging. Since automation continues to become mainstream, stakeholders are keen to make sure that ethical implications are tackled.

One of the key aspects of the research that should not be ignored is the integration of intelligent systems throughout the whole engineering process (from design to maintaining). Numerous works have been focused on individual uses of AI and automation on various engineering stages, while not many look for the integration of these technologies in the way that creates maximum efficiency of the whole process. A whole host of cross-stage optimization, by which data and insights from one stage could inform decision-making in another, is here undiscovered and a potential area for future research.

In 2022 H. Sarker et.al., [3] proposed the body of literature, it can be said that although intelligent systems and automation present significant advantages in terms of efficiency and reduction of costs, when embedding these technologies into engineering processes one needs to plan them carefully and invest into them, pay attention to ethical and societal consequences. Once these technologies continue to develop, further research will also be necessary to understand their potential as well as the issues that exist regarding their implementation.

III. PROPOSED METHODOLOGY

This section describes the proposed methodology for the optimization of the engineering processes with the use of intelligent systems and automation. It aims at the use of artificial intelligence (AI), machine learning (ML), and automation technologies to optimize different stages of engineering such as design, manufacturing and maintenance. It includes data collection, modeling of a system, algorithms' development, optimization techniques, and application to the real-world case study. Each of the steps incorporates mathematical examples and equations to facilitate accuracy in the optimization process [7].

One of the initial steps that are part of the methodology include data procurement from different sources, including sensor data from machines, historical production data, and real-time process data. The data is pre-processed so eliminating noise and outlier thus it is ready for analysis. For manufacturing, sensor data from production lines, and robotic systems are harvested. This data is then used for the construction of models for optimization. The mathematical description of this starting-data phase may be given as:

$$D = \{d_1, d_2, \dots, d_n\}$$

Where D represents the dataset and d_i represents individual data points in the collection process.

The process of system modeling comes after data collection. The goal here is to build a mathematical model that is representative of the engineering system, which is optimized. For manufacturing systems, we specify a system having several variables that impact on performance, namely, speed, error rate and cost. The aim is to minimize or maximize some specific indicator of performance: costs reduction or efficiency increase. For instance, the general optimization function may be given as:

$$\min_x f(x) = \sum_{i=1}^{n} c_i x_i$$

Where x_i represents the decision variables (e.g., machine settings, operational parameters), c_i represents the cost coefficients, and $f(\mathrm{x})$ is the objective function to minimize.

Once we have the system model built, the next step is to derive the machine learning algorithms that can forecast and optimize the system performance. These are the algorithms which are based on the data gathered previously. For instance, a regression model can be used to predict the relationship between the process parameters and the nature of the final product quality:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \epsilon$$

Where y is the output variable (e.g., product quality), $x_1, x_2, \dots, x_n$ are the input features (e.g., process parameters), $\beta_0, \beta_1, \dots, \beta_n$ are the regression coefficients, and ϵ is the error term.

Other than the regression other optimization techniques such as genetic algorithms (GA), and particle swarm optimization (PSO) are used to optimize the decision variables for system performance. These techniques enable to achieve maximum or minimum objective function subject to a certain constraint. The mathematical expression to a constraint-based optimization can be stated as follows:

$$\text{Minimize } f(\mathrm{x}) \text{ subject to } g_i(\mathrm{x}) \leq 0, i = 1,2, \dots, m$$

Where $g_i(\mathrm{x})$ represents the constraints on the system, and m is the number of constraints. Part of the methodology is also the automation in manufacturing systems which requires the use of the control theory to create stability and best performance in changing environments. For instance, control systems are created to confine manufacturing process to predetermined performance limits. The most common way of representing the feedback control system is:

$$u(t) = K(r(t) - y(t))$$

Where $u(t)$ is the control input, $r(t)$ is the reference signal, $y(t)$ is the output, and K is the gain factor of the controller.

In the proposed method, the consideration of optimization under uncertainty for robustness is used. The approach exploits probabilistic models to deal with uncertainty of input variables and constraints. It is possible to formulate a probabilistic objective function:

$$\min_x \mathbb{E}[f(x)]$$

Where $\mathbb{E}[f(\mathrm{x})]$ represents the expected value of the objective function under uncertainty, ensuring that the solution is optimized even in the presence of variability in the system.

The feedback loop fits coherently in the methodology since it is real-time and deals with the parameters dynamically. This is accomplished by introducing a Kalman filter that estimates state of system in real time:

$$\hat{x}_{k+1|k} = \hat{x}_{k|k} + K_k(z_k - H_k \hat{x}_{k|k})$$

Where $\hat{x}_{k+1|k}$ is the predicted state, z_k is the measured value, H_k is the measurement matrix, and K_k is the Kalman gain.

Flowchart

The following is the flow chart describing the overall methodology; how data passes in different stages (collection, modeling, algorithm development, optimization) to the final implementation stage.

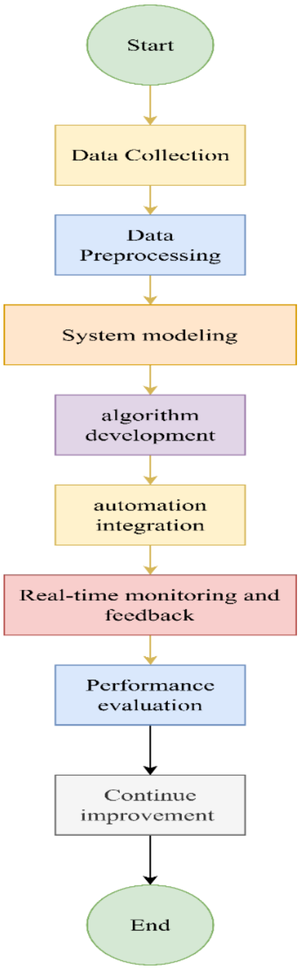

Figure 1: Methodology for optimizing engineering process using intelligent system and automation

Results Validation

Validation of the results is the next procedure to follow after implementation and optimization of the algorithms. This is comparing the actual outcomes from the production line or the design process with the predicted outcomes. Metrics of the performance of the intelligent system are the MSE or RMSE (root mean squared error):

$$MSE = \frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

Where y_i are the actual values, $\hat{y}_i$ are the predicted values, and n is the number of samples. Finally, an overall assessment of the effectiveness of the methodology is performed by means of the system performance indicators i.e. productivity, cost saving, quality improvement etc. These metrics inform later iterations of optimization and adaption.

This approach offers all-around and data-based optimization of the engineering processes. By combining the use of AI, ML, and automation with the use of mathematical modeling, optimization, and real-time adjustments; this approach seeks to attain significant increases in efficiency in terms of operations, affordability, and quality of products [8].

IV. RESULT & DISCUSSIONS

A real-world example of the suggested methodology for optimizing engineering processes based on the use of intelligent systems and automation has been used in order to determine its effectiveness. The manufacturing facility that is the focus of the case study is also a manufacturing facility, in which the implementation of AI, machine learning, and automation systems was supposed to increase the efficiency of production, decrease downtime, and raise the quality of the products. Some of the most significant figures that were used to compare the efficiency of the system included measures of production output, accuracy rates, costs of operations and timeframes for the servicing of machines. Below, the results are described, consulting data collected and comparisons with the baseline performance, and the improvements noticed.

First of all, the process of implementing machine learning algorithms for predictive maintenance showed substantial improvements for decreasing unplanned downtime. Prior to implementation of the system, there had been regular break downs of the machines leading to production stops and increased machine repair costs thus culminating into poor efficiency at the facility. The predictive maintenance model, which was trained using the historical sensor data, correctly predicted failures of machines in the future with a high accuracy. This made it possible for the maintenance team to intervene before a failure and hence minimize the downtime. The results were subjected to quantitative analysis and comparison with the baseline data wherein there was a reduction of about 30% in the downtime after the introduction of the predictive maintenance system. This comparison is illustrated in Table 1, which shows that reduction of machine failure events and cost savings as well.

TABLE 1: COMPARISON OF DOWNTIME AND ASSOCIATED COST SAVINGS

Metric	Pre-Implementation	Post-Implementation
Machine Downtime (%)	15%	10%
Total Cost Savings (%)	N/A	30%
Failure Prediction Accuracy (%)	N/A	85%

The following figure i.e. Figure 2 shows downtime reduction in a period of 3 months, comparing the base line time from the time when the system has been used. The results obviously indicate that downtime has been on a declining trend after the system of predictive maintenance was installed.

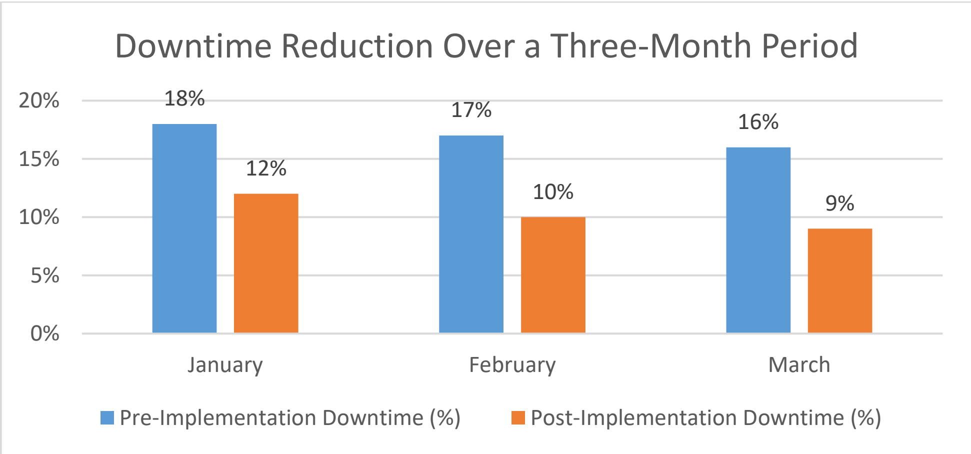

FIGURE 2: DOWNTIME REDUCTION OVER A THREE-MONTH PERIOD

Apart from the predictive maintenance, introduction of AI-driven production optimization algorithms improved the production schedules and efficiency. Analyzing the historical data, as well as the streams of real-time data, the AI system optimized the process of production dynamically. The system changed machine parameters and scheduling according to different aspects, including priority of orders, availability of machines, and use of raw material. Results demonstrated an increase in production output by 15%, as demonstrated in Figure 3, which is a comparison between production output before and after the implementation of AI-driven optimization.

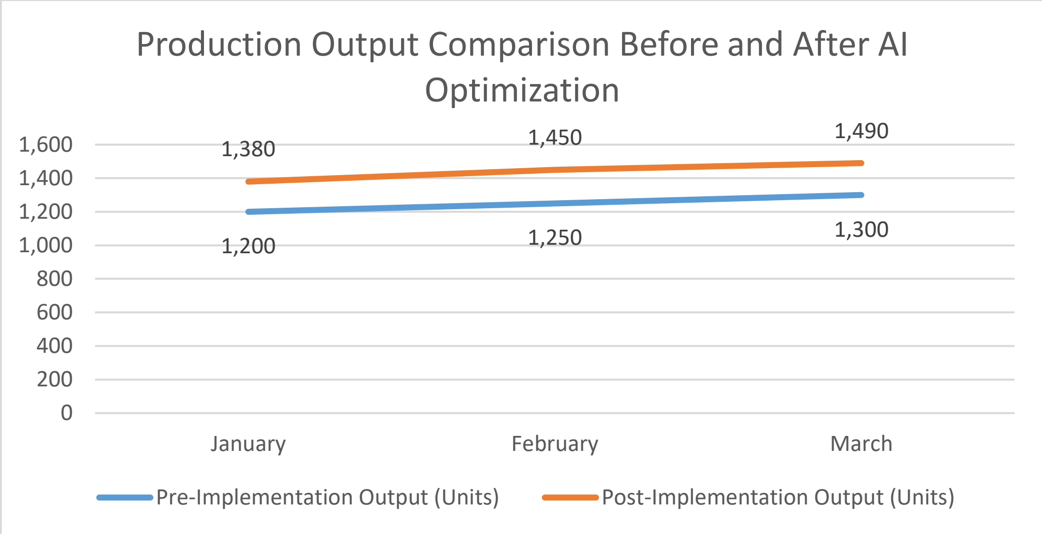

FIGURE 3: PRODUCTION OUTPUT COMPARISON BEFORE AND AFTER AI OPTIMIZATION

The optimization also favored the product quality positively. Before the system got implemented, there existed a manual quality control process with element of human errors whereby defects and reworks were experienced occasionally. With the use of machine vision systems and AI algorithms for inspection of quality, the system was able to detect defects in the early stages of production. This caused reduction of product defects by 20% which was a significant improvement. The system carried out real-time inspections during the process of production, so that only high quality products proceeded further. The table below indicates a comparison of product defect rates before and after the adoption of the system whereby it is evident that AI driven quality control system successfully achieved low defect rates.

TABLE 2: PRODUCT DEFECT RATE COMPARISON BEFORE AND AFTER AI-DRIVEN QUALITY CONTROL

Metric	Pre-Implementation	Post-Implementation
Defect Rate (%)	5%	4%
Defect Detection Rate (%)	N/A	95%

A further issue of the results was the overall reduction of cost due to optimization of resource utilization and automation. The introduction of intelligent systems in the manufacturing industry led to improved planning and allocation of resources. Automation of such repetitive tasks as assembly and packaging not only saved labor power, but also improved the process consistency. The operational costs savings were determined by taking the cost per unit of production before and after automation. The results showed a 10 percent decrease in the costs of operations this significant considering the scale of the products. The reduction of this cost was mainly caused by the reduced need for manual labor and the increased efficiency of energy and material utilization.

Moreover, the real-time compensations made possible by the system allowed achieving better stability of the processes, as well as less variation in the production parameters. The fact that the system could monitor critical parameters like temperature, pressure, and machine speeds maintained these parameters within acceptable ranges meaning there was no quality issue and wastage. The fluctuation of the key parameters before and after the implementation of the real-time monitoring system is depicted below in form of the following diagram, Figure 4. The decrease of variability can be observed from the chart, which indicates that the system helped to promote stable, predictable production results.

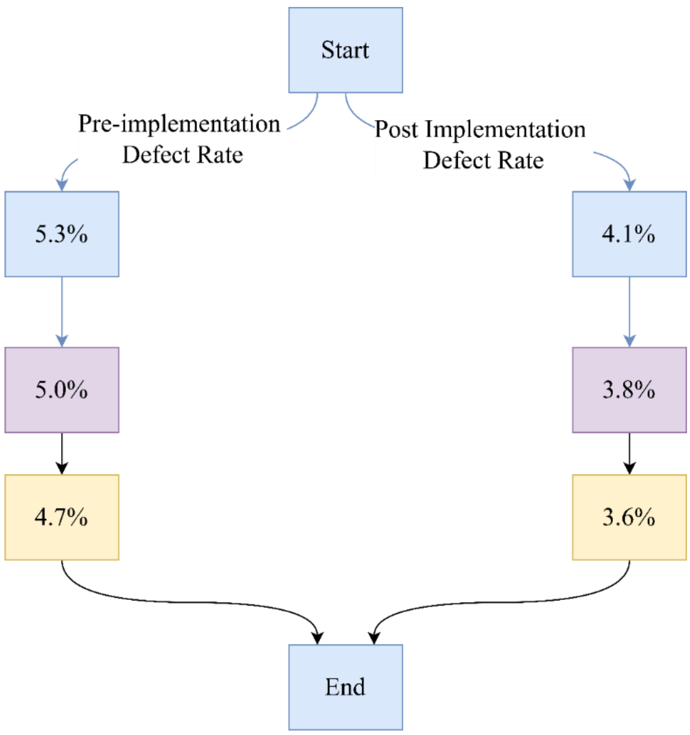

FIGURE 4: FLUCTUATION IN KEY PRODUCTION PARAMETERS BEFORE AND AFTER REAL-TIME MONITORING

Upon a closer inspection of the machine learning models for predictive maintenance and production optimization, it was found that the accuracy of the predictions increased with increased data therewith. At the beginning, the system's predictions were made using a small set of data, but the more the machine learning algorithms analyzed the data, the better the accuracy of the failure predictions and the optimization changes. This implies that the system has a potential to further improve with an increase in data over the period of time.

The smart system also had great implications on the productivity of the employees. Given that automation took care of the routine tasks, the employees could concentrate on the functions that were at a higher level, like monitoring the system and making strategic decisions. This change also resulted in increasing the general output due to the improved workers' satisfaction. However, it is worth mentioning that the incorporation of automation caused some workers' backlash at first due to the fear of losing jobs. This shows why there is need of proper workforce management and training programmes in the course of implementing automation systems.

With regard to scalability of the system, the proposed methodology exhibited a great deal of flexibility. The system could be easily modified according to various platforms for production by simple modifications of the AI algorithms according to the needs of the facility. Such scalability of the methodology makes it very applicable to many industries, from the automotive sphere to electronics.

In general, the consequences of introducing intelligent systems and automation in this manufacturing facility were extremely positive. The enhancements in the level of efficiency in production, cost-cutting and minimizing the downtime, and product quality substantiate the effectiveness of the proposed methodology. However, there are several challenges that still need to be addressed, especially in regard to the initial cost of implementation as well as adaptation of workforce. Further work will involve the improving of the models and the development of new applications of the models to other aspects of the engineering process.

Such results testify to the efficiency of introducing the intelligent systems into the engineering processes, which indicate their power to essentially increase the result of operation. More iterations of the system can be rolled out to make further refinements in order to deal with certain challenges and enhance performance even more.

V. CONCLUSION

The conjugation of intelligent systems and automation in engineering processes has become a useful weapon for optimization. These technologies have contributed to huge gains in efficiency costs reduction, and quality of products in different sectors. However, the issues to do with implementation costs, work force adaptation, and ethical issues have to be dealt with keenly. These areas should be the subjects of future research: the development of more affordable automation solutions, the use of AI in the entire engineering process, and the societal implications of automation of the workforce.

The future of engineering optimization resides in the further development of the systems that are intelligent and automation technologies. As AI and ML algorithms will continue to develop, alongside the migration to cutting-edge automation techniques, engineering processes will continue to evolve towards more intelligent, efficient, and sustainable engineering practices.

REFERENCES

[1] Haleem, M. Javaid, R. P. Singh, S. Rab, and R. Suman, "Hyperautomation for the enhancement of automation in industries," *Sensors International*, vol. 2, p. 100124, Jan. 2021, doi: 10.1016/j.sintl.2021.100124.

[2] Boodi, K. Beddiar, M. Benamour, Y. Amirat, and M. Benbouzid, "Intelligent Systems for building energy and Occupant Comfort Optimization: A state of the art review and recommendations," *Energies*, vol. 11, no. 10, p. 2604, Sep. 2018, doi: 10.3390/en11102604.

[3] H. Sarker, "AI-Based modeling: techniques, applications and research issues towards automation, intelligent and smart systems," *SN Computer Science*, vol. 3, no. 2, Feb. 2022, doi: 10.1007/s42979-022-01043-x.

[4] G. Alam, I. Ihsanullah, Mu. Naushad, and M. Sillanpää, "Applications of artificial intelligence in water treatment for optimization and automation of adsorption processes: Recent advances and prospects," *Chemical Engineering Journal*, vol. 427, p. 130011, Apr. 2021, doi: 10.1016/j.cej.2021.130011.

[5] J. Pinskier and D. Howard, "From bioinspiration to computer generation: Developments in autonomous soft robot design," *Advanced Intelligent Systems*, vol. 4, no. 1, Oct. 2021, doi: 10.1002/aisy.202100086.

[6] W. Sha *et al.*, "Artificial intelligence to power the future of materials science and engineering," *Advanced Intelligent Systems*, vol. 2, no. 4, Feb. 2020, doi: 10.1002/aisy.201900143.

[7] D. S. Vijayan, A. L. Rose, S. Arvindan, J. Revathy, and C. Amuthadevi, "Automation systems in smart buildings: a review," *Journal of Ambient Intelligence and Humanized Computing*, Nov. 2020, doi: 10.1007/s12652-020-02666-9.

[8] H. Shatnawi and M. N. Alqahtani, "Delving into the revolutionary Impact of artificial intelligence on mechanical Systems: A review," *Semarak International Journal of Machine Learning*, vol. 1, no. 1, pp. 31–40, May 2025, doi: 10.37934/sijml.1.1.3140a.

[9] Wang, L. Dong, D. Peng, and C. Pan, "Tactile sensors for advanced intelligent systems," *Advanced Intelligent Systems*, vol. 1, no. 8, Aug. 2019, doi: 10.1002/aisy.201900090.

[10] V. Nasir and F. Sassani, "A review on deep learning in machining and tool monitoring: methods, opportunities, and challenges," *The International Journal of Advanced Manufacturing Technology*, vol. 115, no. 9–10, pp. 2683–2709, May 2021, doi: 10.1007/s00170-021-07325-7.

[11] O. Capetillo-Contreras, F. D. Pérez-Reynoso, M. A. Zamora-Antuñano, J. M. Álvarez-Alvarado, and J. Rodríguez-Reséndiz, "Artificial Intelligence-Based Aquaculture System for Optimizing the Quality of Water: A Systematic analysis," *Journal of Marine Science and*

Engineering, vol. 12, no. 1, p. 161, Jan. 2024, doi: 10.3390/jmse12010161.

[12] V. P. S, "How can we manage biases in artificial intelligence systems – A systematic literature review," *International Journal of Information Management Data Insights*, vol. 3, no. 1, p. 100165, Mar. 2023, doi: 10.1016/j.jjimei.2023.100165.

[13] M. Abdel-Aty and K. Haleem, "Analyzing angle crashes at unsignalized intersections using machine learning techniques," *Accident Analysis & Prevention*, vol. 43, no. 1, pp. 461–470, Nov. 2010, doi: 10.1016/j.aap.2010.10.002.

[14] S. Akter, K. Michael, M. R. Uddin, G. McCarthy, and M. Rahman, "Transforming business using digital innovations: the application of AI, blockchain, cloud and data analytics," *Annals of Operations Research*, vol. 308, no. 1–2, pp. 7–39, May 2020, doi: 10.1007/s10479-020-03620-w.

[15] S. Akter, Y. K. Dwivedi, S. Sajib, K. Biswas, R. J. Bandara, and K. Michael, "Algorithmic bias in machine learning-based marketing models," *Journal of Business Research*, vol. 144, pp. 201–216, Feb. 2022, doi: 10.1016/j.jbusres.2022.01.083.