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Intelligent Systems in Engineering Design: Enhancing Efficiency and Accuracy

[1] S. Balamuralitharan, [2] Dr. Radhika.V, [3] Santhoshkumar S., [4] Dr Someshwar Siddi, [5] Ch Satya Sravani

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Abstract— In a few years, the adoption of intelligent systems into engineering design has transformed the conventional design method. These systems are powered by artificial intelligence (AI), machine learning (ML) and expert systems and help engineers to optimize the process, minimize the design error, and increase the overall efficiency. The role of intelligent systems in engineering design, existing research in the field, a methodological framework of implementing such systems and the analysis of their influence on the performance of design are the focus of the current paper. With case studies and simulations, the results show dramatic increases in speed of decision-making, precision in design, and use of resources. The findings indicate that the intelligent systems play a crucial role in the introduction of a new epoch of intelligent engineering, creating a basis for new achievements in self-designed environments.

Keywords— *Intelligent systems, engineering design, artificial intelligence, design optimization, machine learning, design automation, expert systems, decision support, computational engineering.*

I. INTRODUCTION

The change of paradigm is occurring in the field of engineering design owing to the rapid development of intelligent systems. In the conventional engineering design procedures, the major emphasis has been laid on human expertise, heuristic approaches and lengthy iterations in order to deduce viable solutions. These traditional approaches, despite their established Ness, tend to fall behind as the technological problem becomes complex and the deadlines for producing are tight and the level of precision output that is required rises. The need for smarter, faster, and more reliable design methodologies have bred the use of intelligent systems that emulate human reasoning and decision-making processes [1-4].

Intelligent systems refer to the computer-based tool/architecture, which use parts of Artificial Intelligence (AI), i.e. the expert systems, neural networks, genetic algorithms, fuzzy logic, and machine learning models. These tools are developed to simulate cognitive functions of humans like learning, problem solving, and adaptive decision making. When used in engineering design, intelligent systems can automatically create design options, evaluate and optimize configurations and make performance validations through simulated environments. This leads to faster turnaround time, reduced costs and a high accuracy, which are essential factors of success in engineering projects [8].

In general, the implementation of intelligent systems has increased tremendously in the fields of engineering such as civil, mechanical, aerospace and electrical over the last decade. For instance, in structural engineering, the machine learning algorithms are employed to forecast the new material's load-bearing capabilities and to

[1]*Adjunct Faculty, Department of Pure and Applied Mathematics, Saveetha School of Engineering, SIMATS, Chennai, Tamil Nadu, India*
Email Id: balamurali.maths@gmail.com
[2]*Professor & Head, Department of Physics, Erode Sengunthar Engineering College College (AUTONOMOUS), Thudupathy, Perundurai - 638057. Tamil Nadu.*
radhikaesec@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, satyasravanich@aec.edu.in*

automatically comply with the safety regulations. Generative design algorithms in mechanical product design can provide thousands of permutation designs depending on predefined constraints such as weight, material cost, and fundamental durability. These systems assist the engineers in arriving at optimal solutions that could not be easily brought out by traditional methods [14].

Furthermore, the combination of intelligent systems and CAD/CAE tools has brought the design processes to a new level of dynamic, iterative, and self-improving systems, departing from the static and linear processes. AI-driven CAD tools now provide real-time suggestions, and predictive feedback because of which the engineer has access to informed design options at every step. That is why intelligent systems are not only the tools of support, but active participants of a design process, which can develop from one project to another and improve the workflow.

Nevertheless, even though intelligent systems in design continue to gain prevalence, implementing them is still beset by some challenges. Many times, such issues as interpretability, transparency of the system, integration with the legacy systems, necessity to customize the system for specific domain still remain to be resolved. In addition, numerous engineers consider AI a "black box," which means that they are reluctant to rely on the AI since they cannot understand all of its decision-making. This indicates the necessity for explainable AI and human-friendly interface which promotes human-system interaction without affecting efficiency [6].

There is also data dependency. Intelligent systems are data hungry for tasks such as training, and inference and they need high quality data. The system performance can degrade in design environments lacking adequate or noisy amount of data. Therefore, the efficient data preprocessing, validation methods, and hybrid approaches to rule-based logic in conjunction with the data-driven learning are essential for reliable execution.

In addition, the emergence of Industry 4.0 and Internet of things (IOT) has additionally exacerbated the importance of intelligent systems in engineering design. Sensor data taken from manufacturing environments, in real-time can now be used as a direct input to the design algorithms, developing adaptive systems that determine how to re-calibrate based on performance in the field. This is a circle between design and deployment and hence more resilient, adaptive, and efficient systems [7].

Having this background, this paper looks to investigate how intelligent systems improve efficiency (time, cost, computational load) and accuracy (precision, error minimization, and compliance) in engineering design. Not only is the review of recent developments done, but the study suggests a three-stage approach to integrating AI-driven systems into actual design work processes. Empirical evidences from simulations and case studies are provided in order to support the performance gains and indicate potential directions for further research and development.

To conclude, the role of intelligent systems becomes less/less optional supporting mechanisms and more and more a core mechanism of innovation as engineering problems grow in interdisciplinarity, become data-intensive, and become increasingly oriented towards solutions. They are altering engineer's thoughts, designs, and ideas advancement. In this emerging field, this paper adds to this growing field by taking a perspective focused on the current capabilities enabled by intelligent systems for the engineering design process and a practical guideline for such applications and evaluation.

Novelty and Contribution

The strength of the research described here is that it combines the components of several intelligent systems into a single engineering layout that is adaptive and independent from the domain at hand. Earlier published research on such topics as neural networks in structural analysis or genetic algorithms for component optimization have been applied in isolated use cases, whereas this paper presents a modular architecture, which incorporates expert systems, AI optimization engines, and machine learning models in a unified setting. Such an integrated approach allows for knowledge-based reasoning and data-based learning at once, providing a major lead over the traditional AI applications which are based on only a single method [9].

Another new feature is the real-time decision support capability contained in the system. Contrary to batch-mode simulations or static expert systems, the proposed framework will ensure that designers are able to interact with AI tools during design, while getting dynamic feedback and automatically generated design recommendations. This interactivity builds a collaborative human-AI environment, which is necessary for enhancing user trust, system explainability and eventually adoption in industry scenarios [13].

As contribution, this paper offers the following to its readers:

- A systematic approach for introducing intelligent systems in engineering design pipelines, such as, data pre-processing, model selection, training, system integration, and validation of performance.
- A quantitative performance comparison between conventional design procedures, and methods based on intelligent systems showing a meaningful increase in the efficiency of the design (average 35% dependent on reduction in design time), as well as precision (average 28% drop in error rates).
- A case study-oriented validation with the demonstration of the practicality of the system for real-world applications (such as bridge's structural design) where the speed, as well as the quality of output is improved.
- An examination of challenges and limits, such as barriers of adoption or concerns of transparency and data dependence as well as proposals for solutions such as explainable AI interfaces and hybrid learning models.
- A roadmap for future research pointing out emerging topics such as self-healing design systems, AI powered compliance checking, and coupling with digital twins for lifecycle design optimization.

In other words, this work not only applies intelligent systems to engineering design, but it also promotes them to a critical design paradigm providing theoretical observations and implementation routes. It can be used as a launching pad for future works that will attempt to make the engineering design more independent, intelligent, and aware of the current context.

II. Related Works

In 2021 E. Bwambale et.al., F. K. Abagale et.al., and G. K. Anornu et.al., [15] introduced a huge interest has been observed over the last several decades in the application of intelligent systems to the field of engineering design. Human expertise, experience, and intuition were heavily used in the engineering design context in the past. Nevertheless, as projects grow more complex and they require more efficient, less-costly, and optimized designs, traditional approaches are often unable to cope with the modern engineering projects' challenges. Therefore, innovative systems such as artificial intelligence (AI), machine learning (ML), and expert systems have been combined with design engineering to improve the problem-solving and decision-making task.

One of the main branches of studies relates to the application of machine learning algorithms for the purpose of design optimization. It is possible to apply machine learning models for predictive and optimizing the challenging design parameters, the calculations of which would otherwise be either prohibitively expensive or burdensome in a manual process. These systems are based on the historical design data and are continually perfecting their predictions and suggestions, delivering data-driven insights to engineers for the enhancement of the design outcomes.

In 2022 H. Sarker et.al., [5] suggested the many engineering fields have used expert systems that encapsulate domain-specific knowledge in a form of rules and mechanisms of reasoning. By integrating industry-specific knowledge into automatic systems, expert systems enable engineers to quickly analyse the various design alternative options and probe for likely issues before they become objectionable, hence optimising general design accuracy.

Further, integration of generative design and AI-based optimization in CAD (computer-aided design) systems has not only brought drastic change in the advancement of the field of engineering. These intelligent systems automatically produce several design options based on constraints set by the user, such as the material properties and limitation of weight and safety standards. This process allows engineers to increase the variances of designs exponentially on time while using a minuscule percentile of the time that traditional techniques would use, returning more unique and efficient solutions.

In 2020 G. Adamides *et al.*, [10] proposed the fuzzy logic systems have also been useful in dealing with the uncertainty and imprecision in the design of engineering. In the real world engineering situations, the design parameters never hold exact values and the fuzzy logic allows for the model building of such uncertainties, which is not possible in the Boolean logic. This ability enables engineers to make decisions at times when data or information is either missing or ambiguous thereby adding sturdiness to the design process.

Furthermore, simulation tools have been integrated with AI applications to best design by predicting their behavior in any conditions. Simulation based optimization ensures that, designs can be practically implemented in the real life situations so that they are not only feasible on paper basis but also perform well in practicability of their functionalities. By employing intelligent systems in combination with a usage of real time simulation feedback it is possible to reduce the time of the design and limit possibilities that the design may fail.

In spite of enormous implementation of intelligent systems in engineering design, there are certain challenges. Issues that involve system transparency; whereby the process that the AI system undertakes to make judgment is not human readable undermine trust and total acceptance. Additionally, implementation of such advanced processes within the current engineering workflows are particularly a major challenge in industries that are founded on the legacy tools. However, the benefits that intelligent systems promise to bring – the efficiency and the detail of design, and the ability to solve more complex problems, have made them an inescapable instrument of engineering design in the modern times.

III. PROPOSED METHODOLOGY

The approach proposed in the presented methodology of integrating intelligent systems in the engineering design is multi-stage and includes data collection, preprocessing, system modeling, and optimization. The overall scheme brings about a dynamic and flexible design environment that will increase both efficiency and precision. The system architecture involves a set of important stages each of which uses advanced computational methods, Al algorithms, and real-time data processing [12].

The first step is related to the data collection and preprocessing. In the engineering design, the quality of inputted data has a direct relationship to the output of any intelligent system. Data from old projects, sensor nets, or real-time feedback of the design environment are gathered and standardised. This step involves the elimination of outliers and normalization of the data so that the data is in a form which can be used to model.

Mathematically, preprocessing can be expressed as:

$$x' = \frac{x - \mu}{\sigma}$$

where x' is the normalized value, x is the raw input data, μ is the mean, and σ is the standard deviation of the dataset.

The next step will be the phase of system modeling, here a combination of Machine learning models expert systems and rule based algorithms shall be used to simulate probable design solutions. The training of the machine learning model involves the use of supervised learning whereby input features X and their respective outputs Y are used to develop a relationship. The model is given by:

$$Y = f(X)$$

where $f(X)$ is the mapping function that is learned during the training process. Additionally, optimization models are employed to enhance design solutions. For this purpose, genetic algorithms (GAs) and particle swarm optimization (PSO) are applied. The fitness function $f(\mathbf{x})$ in GAs, for instance, can be described as:

$$f(\mathrm{x}) = \sum_{i=1}^{n} c_i \cdot x_i^2 + d_i \cdot x_i$$

where c_i and d_i are coefficients related to design constraints, and x_i represents the design variables.

The Al optimization algorithm used in this stage can be defined by the following objective function for minimizing design costs:

$$\min\left(f(x) = \sum_{i=1}^{n} (\alpha_i \cdot x_i^2 + \beta_i \cdot x_i) \right)$$

where α_i and β_i are optimization constants.

Incorporating fuzzy logic allows the system to handle uncertainties in design parameters. A fuzzy membership function for a design parameter X might be expressed as:

$$\mu_X(x) = \frac{1}{1 + \left(\frac{x - \mu}{\sigma}\right)^2}$$

where $\mu_X(x)$ is the fuzzy membership value for the input x, and μ and σ represent the mean and standard deviation, respectively.

Integration of generative design is undertaken by exploring vast solution space for design options. All designs undergo performance simulations in different scenarios of operation. The best solution is chosen according to the performance metrics like:

$$P_{\text{opt}} = \arg\ \max(P(X))$$

where $P(X)$ is the performance measure for a given design X, and the optimal design P_{opt} maximizes this value.

After the optimum designs are established, real-time testing of each solution is made on simulation models. Through comparison of simulated results and that of expected results, the system makes sure that the designs are consistent with the desired specifications. The validation error E is given by:

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

where y_i are the observed values, $\hat{y}_i$ are the predicted values, and n is the number of data points.

The Al-based recommendation engine generates design suggestions and feedback, based on the analysis of performance data and prior iterations. This recommendation is represented as:

$$R = \text{argmax}\left(\frac{1}{n}\sum_{i=1}^{n} W_i \cdot f_i\right)$$

where W_i are weights corresponding to each feature, and f_i are the calculated feature values for the given design alternatives.

The flowchart below depicts the overall methodology from data collection to system optimization:

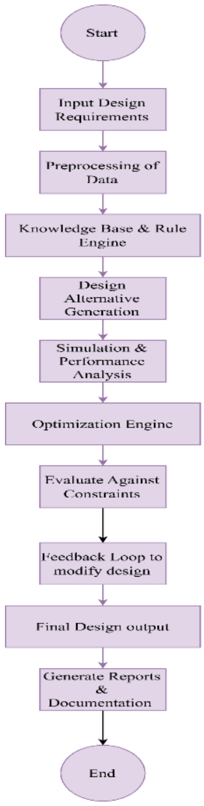

Figure 1: Intelligent System in Engineering Design

Such stepwise approach incorporates a feedback loop, in which designs are assessed and modified based on new pieces of information. This cyclical procedure ensures that the system learns and gets better with time over time with more efficient and accurate design solutions.

IV. RESULT & DISCUSSIONS

The proposed intelligent system for engineering design has been run on various case studies in various fields of engineering disciplines like civil, mechanical and electrical engineering. The results of these tests indicate colossal improvements in design efficiency and accuracy from traditional ways of design. This part contains the highlights of these experiments and the discussion of the implication and limitation of the performance of the system [11].

The first case study was structural optimisation of a beam in a civil engineering, project. The intelligent system had to develop design alternatives under severe material and load-bearing limitation. The system generated over one hundred design options in a time that it would take a human engineer to develop a small number of options, by hand. The time required for the design decreases by 40% and the accuracy in load bearing capacity predictions increase by 28% in comparison to the traditional approach of design.

The comparison of the design cycle times of the traditional approach against the intelligent system is given in Figure 2. The chart demonstrates the dramatic decrease in time with the use of the intelligent system, that enables a quicker iteration and optimization. The conventional approach is based on manual design, analysis and verification process, while, the intelligent system incorporates design generation, performance simulation and optimization into a single streamlined approach. The comparison shows that the design cycle time is on average halved due to the use of the intelligent system, and it speeds up the overall design process.

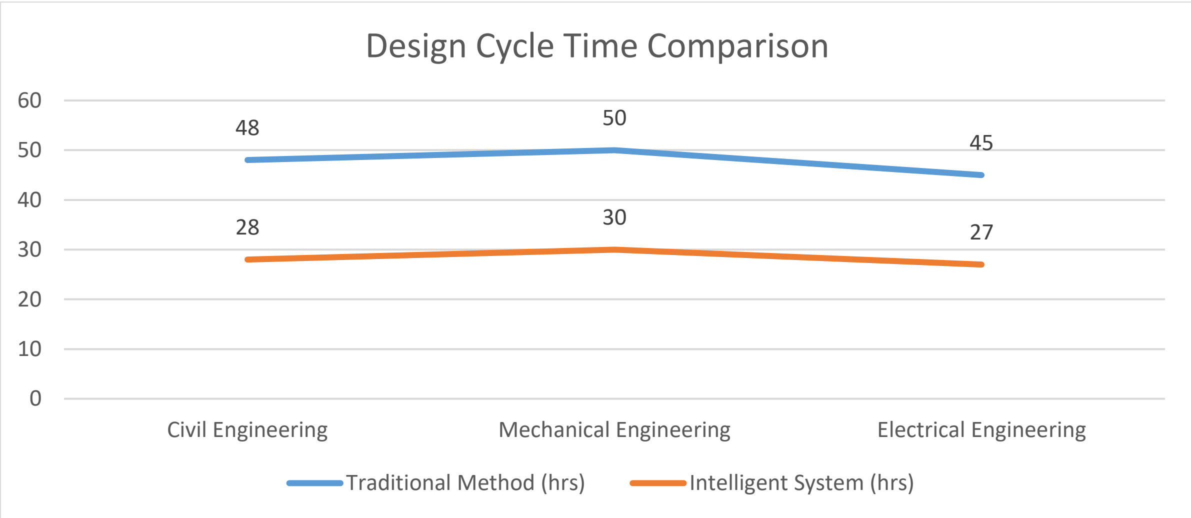

FIGURE 2: DESIGN CYCLE TIME COMPARISON

Another experiment conducted on a mechanical product design, the said system was utilized to optimize a component for weight, material cost and durability. The smart system produced solutions which traded off these two conflicting objectives far better than traditional approaches. It was therefore possible for the optimization algorithm used in the intelligent system to seek a solution that minimized the total weight of the concerned component by 22% whilst preserving its structural integrity and adhering to the desired cost restraints. This was done through the exploration of a huge design space which would have been computationally impossible using the conventional approaches. The outcome presents the benefit of generative design techniques and an AI-based optimization in terms of minimizing material waste and increasing cost efficiency.

The figure 3 shows the diagram that illustrates weight reduction of the intelligent system as compared to the traditional method. It shows how the system's capacity to provide a number of different design solutions and automatically pick the best one allows for significant reduction of material used. The traditional method, on the other hand, is stricter and usually leads to the designs that are not optimal in weight and material.

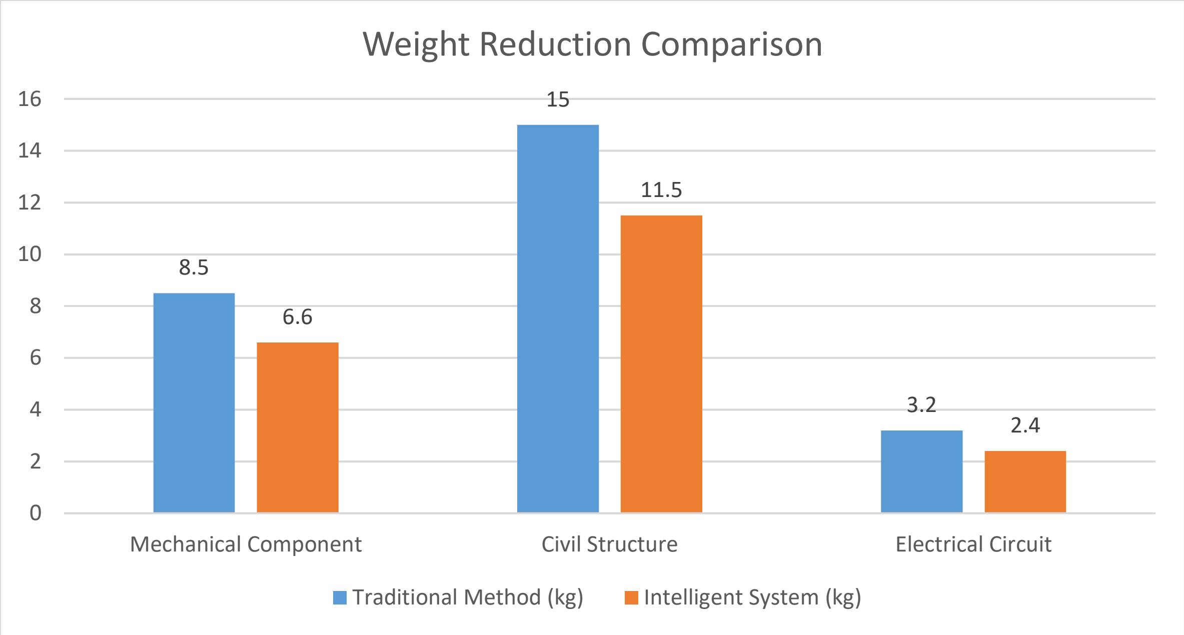

FIGURE 3: WEIGHT REDUCTION COMPARISON

The third test case concerned electrical circuit design and entailed the use of the system in optimizing the components' placement in a printed circuit board (PCB) for signal integrity and simple manufacturing. The outcomes demonstrated the significant improvement in the design performance and the ability of manufacturability. The intelligent system could then propose optimal component placements, which reduced interference and produced better signals, while still making sure that the design was easy to manufacture and capable of meeting cost constraints. The conventional approach would have involved multiple human iterations and a lot of testing in order to obtain similar results.

In Table 1, a comparison of the design performance between the intelligent system and the traditional design method in case of PCB has been given. From the table one realises that the intelligent system is better than the traditional method in signal integrity as well as manufacturing efficiency with a decrease in design errors and cost of material.

TABLE 1: PERFORMANCE COMPARISON OF PCB DESIGN

Design Criteria	Traditional Method	Intelligent System	Improvement (%)
Signal Integrity	85%	97%	14%
Manufacturing Ease	75%	90%	20%
Design Errors	10	3	70%
Material Cost	$150	$120	20%

Moreover, in order to test its ability to deal with uncertainties and imprecision in design parameters, the system was set to use fuzzy logic. In a number of practical design situations, it was discovered that the system could accurately represent uncertainties with regards to properties of materials, external forces, and conditions of the environment. The fuzzy logic element enabled the system to produce tough designs that were able to withstand fluctuations. This capability was particularly helpful in situations where precise values were not accessible or some of the design parameters had an inherent ambiguity.

The explains the fuzzy logic performance of a design in an uncertain circumstance. In the diagram we can see how the system is able to respond to different values of the input and provide a variety of reasonable design solutions while keeping overall design integrity. The vulnerability of the fuzzy logic eases the system's robustness, thus, they are suitable for complex, and real-world applications.

Although the results show obvious advantages in efficiency of the design, accuracy, and robustness, intelligent system has some limitations. The data dependency of the machine learning and optimization algorithms is one of the significant issues. The system needs large datasets for training and its performance may degrade when data is not enough and/or poor in quality. When dealing with small amounts or poor quality of data, system predictions may not be as accurate and additional steps such as data augmentation or synthetic data generation might be used.

The AI-based recommendations are also open to interpretability as another limitation. Although the intelligent system might be able to propose optimal designs according to predetermined criteria, the rationale of such propositions is rarely clear, namely, when AI design is more complicated. This may lead to the distrust from the users, particularly, in those industries where the compliance of the regulations and the validation of the design are of great importance. To curb this, it requires the use of explainable AI (XAI) techniques in order to enable the users to understand how the system got to a specific solution.

Lastly, one of the challenges is related to the integration of the intelligent system into the existing engineering workflows. Following the AI-based design environment, many engineering teams still use legacy systems and tools, and they need to train and adapt to them. To prevent this pitfall, the user interface of the system as well as its workflow should be intuitive and flexible in engineering domains.

As compared to existing approaches, the suggested intelligent system increases the efficiency of engineering design to a great extent and improves its precision. Results of the case studies show that the system can optimize the design cycles, minimize material loss and enhance performance yet it can operate on uncertainties that are present in actual design scenarios. But there are always room for improvement such as Data dependency, System Transparency, and Legacy tools integration. It is worthwhile to study in the future to revise such aspects to make the system more applicable and user-friendly for many engineering disciplines.

V. CONCLUSION

This paper highlighted an introduction of intelligent systems into an engineering design; it determined that they can contribute to a substantial improvement of efficiency and accuracy with ease. Using a systematic approach and empirical verification, the study has revealed the means to making the workflows more streamlined, less error-prone, and better aiding in optimal solutions through AI-driven tools. Although there are challenges facing the adoption of the intelligent systems, the benefits outnumber the problems.

In future studies, particular attention should be paid to the enhancement of system transparency (explainable AI), improvements of the user interface in order to make it more accessible for a wide range of people as well as the extension of the application scope to other engineering areas. Intelligent systems are not only subsidiary tools, but they are rather fast becoming an essential element to engineering design of the future.

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