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Smart Algorithm Applications in Mechanical Engineering and Physical Sciences for Optimizing Systems and Materials

Ali Soluman Ali Hassien[1*], **Nuri Salem Ali Abosetah**[2]
[1]Department of Electronic Engineering, Higher Institute of Science and Technology -Tamzawa, Wadi Al-Shati, Fezzan, Libya, [2]Department of Mechanical Technology, Higher Institute of Science and Technology -Tamzawa, Wadi Al-Shati, Fezzan, Libya
[1]alisuliemen@gmail.com, [2]melad25111985@gmail.com

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***Corresponding Author**

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ABSTRACT

The increasing complexity of modern engineering systems and the demand for efficient, cost-effective, and high-performance designs have driven the adoption of intelligent computational strategies in mechanical engineering and physical sciences. Traditional simulation and optimization techniques often struggle with nonlinear, multi-objective problems that span both material and structural design spaces. This study aims to develop a unified smart algorithmic framework capable of optimizing both mechanical systems and material properties concurrently. The research focuses on integrating data-driven models with physics-informed techniques to improve predictive accuracy, computational efficiency, and practical applicability. The proposed framework combines artificial neural networks (ANNs), physics-informed neural networks (PINNs), genetic algorithms (GAs), and Bayesian optimization to form a hybrid multi-objective optimization system. A case study on an electric vehicle (EV) suspension system is used to validate the approach. Surrogate models were trained on finite element analysis (FEA) data and applied within a Pareto optimization loop to explore trade-offs among mass, fatigue life, and material cost. The framework achieved a 27% reduction in structural mass, a 35% increase in fatigue life, and a 13% decrease in material cost. Surrogate models attained R^2 values exceeding 0.90, with validation showing less than 5% deviation from FEA results. Sensitivity analysis confirmed design robustness under input variation. The findings demonstrate the effectiveness of smart algorithms in co-optimizing systems and materials. The proposed framework enhances the speed, accuracy, and physical validity of intelligent engineering design.

INTRODUCTION

In recent decades, the increasing complexity of engineering systems and the demand for high-performance materials have driven a significant transformation in the methodologies employed within mechanical engineering and physical sciences. Traditional analytical and numerical approaches, while foundational, often fall short when addressing nonlinear, high-dimensional problems or real-time system optimization. In this context, smart algorithms—particularly those rooted in computational intelligence such as machine learning (ML), genetic algorithms (GA), deep learning (DL), and swarm optimization—have emerged as powerful tools capable of enhancing simulation, prediction, and system design across engineering disciplines (Hua et al., 2023).

Mechanical engineering involves the design, analysis, and optimization of systems that are frequently subjected to dynamic forces, environmental variations, and multi-objective constraints. Physical sciences, on the other hand, focus on the understanding of natural phenomena, including material behavior, energy transformation, and atomic-scale interactions. Both fields generate vast amounts of data and require complex modeling techniques to derive actionable insights. The application of smart algorithms in these areas allows for the automation of analysis, the development of data-driven predictive models, and the optimization of performance metrics beyond human capabilities (Carleo et al., 2019). Several studies have demonstrated the benefits of using smart algorithms in isolated domains. For example, artificial neural networks (ANNs) have been employed to predict material fatigue and crack propagation with high accuracy, while genetic programming has been utilized for system control and structural health monitoring (Zhang et al., 2016).

In material sciences, deep learning models have significantly accelerated the discovery of advanced materials by learning from experimental and simulation data (Choudhary et al., 2022). Furthermore, swarm intelligence approaches

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such as Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) have proven effective in solving complex thermal and fluid dynamic problems (Ma et al., 2013).

Despite these advancements, most existing research tends to remain confined within individual disciplines, rarely addressing the potential of cross-domain integration of computational techniques. This lack of interdisciplinary application represents a critical research gap. The absence of unified frameworks that bridge mechanical engineering and physical sciences through smart algorithms limits the scope of innovation and the generalizability of algorithmic solutions. A more holistic approach is needed—one that applies a common computational strategy to optimize systems and materials in tandem, ultimately enabling more efficient and intelligent engineering solutions. To address this gap, the present study investigates the integrative use of smart algorithms across both mechanical engineering and physical sciences. The main objective is to demonstrate how a hybrid computational framework can enhance predictive capabilities, accelerate design and analysis processes, and reduce development costs. By combining case studies in structural mechanics and material modeling with advanced algorithmic strategies, the paper provides evidence of measurable improvements in accuracy, efficiency, and adaptability. The contribution of this research is twofold. First, it introduces a comprehensive methodology that unifies different branches of computational intelligence for solving multidisciplinary engineering problems. Second, it presents empirical results that validate the effectiveness of smart algorithms in optimizing both mechanical systems and material innovations. Through this work, we aim to support the ongoing evolution of computational engineering practices and contribute to the broader discourse on intelligent system design and scientific computing.

LITERATURE REVIEW

The integration of smart algorithms into mechanical engineering and physical sciences has profoundly reshaped research practices, system design, and problem-solving strategies. As engineering systems become increasingly complex and the demand for precision and efficiency grows, conventional methods such as finite element analysis (FEA), computational fluid dynamics (CFD), or traditional empirical modeling face notable limitations in scalability, adaptability, and computational cost. In contrast, computational intelligence methods—encompassing artificial neural networks (ANNs), genetic algorithms (GAs), support vector machines (SVMs), deep learning (DL), and hybrid models—are capable of learning from data, modeling nonlinear systems, and optimizing multi-variable objectives. This section surveys recent and influential literature that explores these applications, with a focus on cross-domain utility in mechanical systems and materials science.

Gao et al. (2021) presented a hybrid deep learning model that combines convolutional neural networks (CNNs) and long short-term memory (LSTM) units to monitor and diagnose faults in rotating machinery. Their approach uses vibration signal data as input and captures both spatial and temporal dependencies, resulting in a diagnostic accuracy exceeding 98%. This method significantly outperforms traditional FFT-based and time-domain analysis tools, especially in noisy industrial environments. The study demonstrates the potential of hybrid DL frameworks in predictive maintenance and condition monitoring, areas critical to mechanical engineering.

In the domain of energy systems, Brandi et al. (2020) utilized reinforcement learning (RL) to develop a self-learning control policy for heating, ventilation, and air conditioning (HVAC) systems. By interacting with a building's energy model, the RL agent learned to optimize energy consumption while maintaining thermal comfort. The study reported a 17% reduction in energy use compared to conventional rule-based controllers. This work exemplifies the real-time adaptability of smart algorithms in dynamic systems, highlighting their potential to increase operational efficiency in mechanical infrastructures.

Meanwhile, materials science research has also witnessed transformative applications of smart algorithms. Roy et al. (2023) introduced a generative adversarial network (GAN)-based framework to design high-entropy alloys (HEAs). By training the GAN on a dataset of known alloy compositions and their properties, the model could generate novel combinations with desirable strength and ductility characteristics. This reduced reliance on expensive and time-consuming experimental trials, illustrating how AI can drastically accelerate materials discovery and innovation pipelines. Similarly, Ishiyama et al. (2024)applied Bayesian optimization to guide the search for optimal thermoelectric materials. The method involves training a surrogate model to predict the efficiency of new material combinations and iteratively updating it as new data becomes available. Their results demonstrated a fivefold increase in discovery speed, validating the efficacy of smart search algorithms in navigating large, multidimensional chemical design spaces.

At the intersection of engineering and material design, Arshad et al. (2025) proposed a multi-objective evolutionary algorithm for joint mechanical-material system optimization. Their work focused on an electric vehicle (EV) suspension system, integrating both structural performance and fatigue resistance into a unified optimization problem. The hybrid algorithm successfully identified design trade-offs, offering engineers a more balanced and informed decision-making tool. This study underscores the advantages of simultaneously addressing mechanical

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behavior and material constraints using advanced computation.

Sunil and Sills (2024) introduced a novel approach by combining physics-informed neural networks (PINNs) with finite element methods to simulate fluid-structure interactions (FSIs) in biomedical devices, such as artificial heart valves. Their framework preserved the governing physical laws within the neural network training process, resulting in simulations that were both accurate and computationally efficient. This method bridges the gap between data-driven models and classical physics, reinforcing the value of hybrid strategies in multi-physics problems.

Across these studies, several patterns emerge. First, smart algorithms are increasingly preferred over traditional numerical methods due to their learning capacity, robustness, and speed. Second, hybrid and interdisciplinary approaches such as combining AI with physics-based models are proving especially effective for solving real-world engineering challenges. However, despite the progress, a critical limitation remains: most research is confined to domain-specific problems and lacks generalizable frameworks that integrate across mechanical and physical sciences. This presents an opportunity to explore a unified computational approach that can optimize systems and materials concurrently, addressing both design and performance requirements. In this regard, the current study fills a vital gap by proposing a comprehensive algorithmic framework that combines advanced smart techniques and applies them across different engineering domains. The work builds upon the strengths of earlier studies while emphasizing the benefits of convergence, scalability, and adaptability characteristics essential for next-generation engineering systems.

The core issue is that current intelligent algorithm applications in engineering are typically fragmented and limited to specific, isolated problems. There is a lack of integrated, scalable, and adaptive frameworks that leverage smart algorithms across the dual domains of mechanical engineering and physical sciences. Traditional methods are insufficient in capturing nonlinear, high-dimensional relationships, while current AI-based solutions lack cross-domain generalizability. Therefore, a new computational framework is critically needed one that synthesizes machine learning, metaheuristics, and hybrid algorithms to optimize engineering systems and material properties comprehensively

METHOD

This research adopts a comprehensive and interdisciplinary methodology that integrates data-driven algorithms, physics-based modeling, and optimization techniques to address complex problems in mechanical system design and materials innovation. The methodology is organized into five major stages: (1) problem formulation, (2) data acquisition and preprocessing, (3) smart algorithm architecture and design, (4) simulation and multi-objective optimization, and (5) validation and performance evaluation.

Problem Formulation

The formulation of the problem begins with the selection of a representative engineering system that requires the integrated consideration of both mechanical behavior and material characteristics. In this study, the chosen case is the optimization of an electric vehicle (EV) suspension system, which is well-suited due to its inherent complexity and the necessity to fulfill multiple, often conflicting objectives. These objectives typically include the need to ensure mechanical robustness, maximize fatigue life, minimize structural weight, and reduce material cost. Furthermore, the performance of such a system is closely dependent on the chosen materials, making it a prime candidate for demonstrating the synergy between smart algorithmic optimization and material innovation.

The optimization problem is structured as a multi-objective formulation, defined by three primary objective functions: (1) minimizing the total mass of the suspension system, (2) maximizing stiffness to enhance ride quality and handling, and (3) optimizing fatigue life to ensure long-term durability under varying load conditions. Mathematically, the problem can be represented as follows:

$$\text{Minimize x } \{f_1(x), f_2(x), f_3(x)\}, \text{ subject to: } g_i(x) \leq 0, h_j(x) = 0$$

In this formulation, $f_1(x)$, $f_2(x)$, and $f_3(x)$ represent the objective functions corresponding to mass, stiffness, and fatigue life, respectively. The terms $g_i(x)$ denote inequality constraints (e.g., limits on maximum stress, deformation, or cost), while $h_j(x)$ represent equality constraints (e.g., geometric or manufacturing constraints). The design variable vector x may include geometric parameters, material choices, and processing conditions. The ultimate goal is to identify Pareto-optimal solutions that provide the best possible trade-offs among the objectives while satisfying all system constraints.

Data Acquisition and Preprocessing

To support the development and training of smart algorithms within the optimization framework, this study relies on two primary classes of data: mechanical simulation data and material property data. Mechanical simulation data are

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obtained through structural and dynamic analyses conducted using advanced finite element analysis (FEA) tools such as ANSYS and Abaqus. These simulations model the response of the EV suspension system under realistic operational scenarios, capturing key parameters such as stress distribution, modal frequencies, deformation profiles, and fatigue cycles. The simulations are performed across a range of load conditions and material configurations to generate a comprehensive dataset for model training.

Materials property data are sourced from authoritative experimental databases, including the ASM Materials Information database, and augmented with values extracted from peer-reviewed scientific literature. The dataset includes critical material attributes such as density, elastic modulus, yield strength, fracture toughness, thermal expansion coefficient, and fatigue resistance. In cases where direct data is unavailable, surrogate modeling techniques or interpolation methods are applied to estimate missing values reliably.

1. Prior to model development, all data undergo rigorous preprocessing to ensure quality and suitability for algorithmic processing. This includes:
2. Normalization and scaling of all variables to a standardized range (e.g., [0, 1]) to facilitate faster convergence during algorithm training and to eliminate numerical instabilities.
3. Dimensionality reduction using Principal Component Analysis (PCA) to isolate dominant features and minimize redundancy or noise in high-dimensional datasets. This step enhances the efficiency and generalization capability of the models.

Outlier removal and missing data imputation, which are critical to preserving data integrity. Outliers are detected using statistical techniques such as Z-score analysis and removed to prevent model distortion. Missing values are estimated using nearest-neighbor or regression-based imputation methods. This structured approach to data acquisition and preprocessing ensures a robust foundation for the smart optimization framework developed in subsequent sections. It allows the algorithms to learn meaningful relationships and patterns from real-world data, thereby improving the reliability and interpretability of the final design outcomes.

Smart Algorithm Architecture and Design

To address the multi-objective optimization problem involving mechanical performance and material innovation, this study adopts a hybrid smart algorithm framework that integrates several advanced computational intelligence techniques. The architecture is designed to exploit the complementary strengths of machine learning models, metaheuristic optimizers, and physics-informed strategies, ensuring accurate prediction, efficient search, and physical consistency.

The core components of the framework include Artificial Neural Networks (ANNs), Genetic Algorithms (GAs), Bayesian Optimization, and Physics-Informed Neural Networks (PINNs). ANNs are employed as surrogate models to approximate expensive simulations by learning the nonlinear relationships between inputs design parameters and output performance metrics. These models significantly reduce computation time while maintaining high prediction accuracy.

Genetic Algorithms are used as the primary global search mechanism to explore the design space. GAs are well-suited for high-dimensional, non-convex optimization problems and are capable of generating diverse solutions through selection, crossover, and mutation operations. To accelerate convergence and avoid unnecessary evaluations, Bayesian Optimization is applied as a meta-learning layer that guides the GA toward promising regions of the design space using a probabilistic surrogate model (e.g., Gaussian Process). Furthermore, PINNs are incorporated to enforce the physical laws governing mechanical and thermal behavior within the learning process. By embedding differential equations (such as elasticity, heat transfer, and structural dynamics equations) into the neural network's loss function, PINNs ensure that predictions remain physically consistent, even in data-scarce regions. This hybridization of learning and physics leads to improved model interpretability and reliability.

The overall architecture is modular and extensible, allowing for seamless integration of new algorithms or domain-specific modules. Hyper parameters such as learning rate, population size, mutation rate, and convergence criteria are fine-tuned using cross-validation techniques and grid search. The system is implemented using Python (TensorFlow, Scikit-learn, DEAP) and MATLAB environments to ensure compatibility with existing engineering simulation platforms.

This smart architecture serves as the computational engine of the proposed framework, balancing accuracy, efficiency, and interpretability while enabling real-time exploration of trade-offs in multidisciplinary engineering design problems.

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Simulation and Multi-Objective Optimization

Following the development of the smart algorithm architecture, the next phase in the methodology involves integrating the trained models within a simulation and optimization platform. This framework is designed to support multi-objective optimization by evaluating trade-offs between competing design criteria, such as structural mass, fatigue life, stiffness, and material cost. The system leverages the computational efficiency of surrogate models while preserving the accuracy of high-fidelity simulations through targeted validation. The simulation environment is built using a combination of Python and MATLAB toolchains, incorporating libraries such as TensorFlow for neural networks, DEAP for evolutionary computation, and custom scripts for finite element post-processing. This integration allows the platform to perform large-scale parametric studies while maintaining a close link with physical modeling.

The optimization process is structured around the Non-dominated Sorting Genetic Algorithm II (NSGA-II), a widely recognized algorithm for handling multi-objective problems. NSGA-II is selected for its ability to maintain a diverse population of solutions and construct Pareto-optimal fronts, enabling designers to explore the full range of design trade-offs without predefining objective priorities. The algorithm operates on a population of candidate designs, evolving them across generations based on selection, crossover, and mutation operators. At each iteration, surrogate models (ANNs and PINNs) are used to rapidly estimate performance metrics, significantly reducing computational overhead.

The objective functions considered in this study include:

1. Minimization of system mass, to improve energy efficiency and performance.
2. Maximization of fatigue life, to enhance structural durability and reliability under cyclic loads.
3. Minimization of material cost, ensuring economic feasibility of the design.

These objectives are subject to a series of constraints derived from engineering standards and simulation outputs. Constraints include allowable stress levels (based on yield strength), displacement limits (related to suspension travel), and modal frequency ranges (to avoid resonance with typical road-induced vibrations). To ensure that the optimization remains grounded in physical realism, constraint violations are penalized within the fitness function, and the predictions from data-driven models are continuously calibrated against FEA and analytical models at strategic points. In this way, the optimization loop balances speed with accuracy, focusing computational effort on feasible and high-potential design regions.

The final output of this phase is a Pareto front representing a spectrum of optimal trade-offs. From this set, decision-makers can select solutions that best align with application-specific priorities, such as minimizing cost for mass-market EVs or maximizing fatigue resistance for high-performance applications. This simulation-optimization loop is a central pillar of the proposed framework, transforming a traditionally time-consuming and manually intensive design process into a smart, automated, and insight-driven engineering workflow.

Validation and Performance Evaluation

The final stage of the methodology involves the rigorous validation and performance evaluation of the proposed smart algorithmic framework. This step is essential to ensure that the predicted outputs generated by the surrogate models, as well as the solutions obtained through the multi-objective optimization process, accurately reflect real-world mechanical behaviors and material responses. Multiple validation strategies are employed to assess the reliability, robustness, and generalizability of the proposed computational approach. Firstly, comparative validation is conducted by benchmarking the optimized solutions against high-fidelity finite element analysis (FEA) results. Selected design configurations from the Pareto front are re-simulated in full-scale FEA environments to evaluate their stress distribution, deformation behavior, and fatigue life under operational load scenarios. The predicted values from the artificial neural networks (ANNs) and physics-informed neural networks (PINNs) are compared against these results using standard error metrics such as the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and coefficient of determination (R^2). The majority of predictions showed deviations of less than 5%, indicating strong agreement between the surrogate models and physics-based simulations. Secondly, cross-validation is employed during the training of data-driven models. K-fold cross-validation (typically with k =5) is used to assess the generalization capability of the models and prevent overfitting. This technique divides the dataset into training and validation folds, ensuring that each subset of the data contributes to both model training and error estimation. The average R^2 values across all folds exceeded 0.90 for key performance indicators such as mass prediction, fatigue life estimation, and cost assessment. To evaluate the framework's resilience under uncertain or variable conditions, sensitivity analysis is performed. This involves perturbing key input parameters—such as material properties, loading conditions, and geometric dimensions—within a defined range (typically ±10–20%) to assess the effect on output metrics. The analysis revealed that the optimized designs maintained performance stability, with less than 7% variation in fatigue life and

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under 3% variation in structural mass, confirming the robustness of the design recommendations. Furthermore, external validation is conducted by comparing the framework's predictions with published experimental results and case studies from the literature. For instance, the material behavior of selected alloy composites and structural response of lightweight suspension systems were validated against empirical benchmarks from peer-reviewed sources. These comparisons helped establish the external credibility of the model and confirmed that the proposed approach aligns well with established engineering knowledge. Finally, the overall computational efficiency of the framework is assessed. Results showed that the use of surrogate modeling and Bayesian optimization reduced total optimization time by over 60% compared to conventional simulation-only workflows. This demonstrates the practical viability of the proposed system for time-sensitive design tasks in industrial environments. The validation and performance evaluation process confirms that the proposed smart algorithmic framework is both accurate and dependable. It provides a solid foundation for further application in broader engineering contexts and supports its adoption as a reliable tool for intelligent system and material co-design.

RESULT

The proposed smart algorithmic framework was applied to the optimization of a multi-objective engineering design problem involving an electric vehicle (EV) suspension system. The outcomes are presented in three key dimensions: optimization effectiveness, surrogate model performance, and engineering implications, supported by computational validation and sensitivity analysis. These results demonstrate the efficacy and generalizability of the hybrid artificial intelligence (AI) approach in enhancing mechanical design and material selection processes.

Optimization Performance and Design Improvements

The multi-objective optimization process, guided by the NSGA-II algorithm in conjunction with surrogate models and Bayesian optimization, successfully generated a diverse set of Pareto-optimal solutions. These solutions enabled trade-off analysis among the primary design objectives—minimization of structural mass and material cost, and maximization of fatigue life. Among the Pareto set, the best-performing configuration achieved a 27% reduction in system mass, from 12.4 kg to 9.1 kg, which contributes directly to improved energy efficiency and reduced vehicle weight. Simultaneously, fatigue life was improved by approximately 35%, extending the component's lifespan under cyclic loading from 180,000 to 243,000 cycles. Material cost was also reduced by 13%, confirming the economic viability of the optimized solutions.

The optimization process exhibited stable convergence within 50 generations, indicating high computational efficiency. Notably, the diversity of solutions along the Pareto front enabled designers to evaluate trade-offs and make informed decisions based on application-specific constraints and performance priorities. The use of Bayesian optimization enhanced convergence by strategically focusing the search on promising regions of the design space, reducing the total number of required function evaluations by over 60% compared to traditional evolutionary strategies.

Surrogate Model Accuracy and Computational Efficiency

The artificial neural networks (ANNs) employed as surrogate models demonstrated high predictive accuracy and generalization capability. Trained on a dataset comprising over 2,500 simulation results derived from finite element analysis (FEA), the ANNs achieved R^2 values of 0.94 for mass prediction, 0.91 for fatigue life, and 0.89 for material cost. These results indicate that the models were able to capture the nonlinear and multidimensional relationships between input design variables and output performance metrics.

The integration of physics-informed neural networks (PINNs) provided an additional layer of reliability by incorporating governing physical laws directly into the model structure. This approach significantly improved the physical validity of the surrogate predictions, particularly in data-sparse regions of the design space. The PINNs showed consistent compliance with mechanical equilibrium, stress-strain relationships, and geometric compatibility, thus reducing the likelihood of producing non-physical solutions. Furthermore, the combination of ANNs and PINNs led to a marked improvement in computational efficiency. While full FEA simulations required several minutes per design evaluation, the trained surrogate models were capable of delivering near-instantaneous predictions with negligible computational cost. This acceleration enabled extensive parametric studies and supported iterative optimization at a scale that would be impractical using traditional simulation-only approaches.

Validation, Sensitivity Analysis, and Engineering Relevance

To validate the accuracy and robustness of the optimized solutions, selected configurations from the Pareto front were re-evaluated using high-fidelity FEA. The results confirmed that the surrogate model predictions deviated by less than 5% from the FEA results across key metrics, including stress distribution, deflection, and fatigue life. This high

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level of agreement reinforces the reliability of the proposed framework for real-world engineering applications.

A sensitivity analysis was conducted to evaluate the stability of the optimization results under varying input parameters. By introducing ±20% perturbations to load magnitudes, material property values, and geometric parameters, it was observed that the optimized designs maintained their structural integrity and performance. The fatigue life varied by no more than 7%, and mass predictions fluctuated within 3%, indicating that the proposed framework is robust and resilient to moderate uncertainties in input data. From a practical engineering perspective, the optimized suspension system exhibited several key advantages. The peak von Mises stress in the component was reduced by 22%, mitigating the risk of stress concentrations and failure. The first natural frequency increased by 38%, distancing the component from potential resonance zones and improving vibrational performance. The optimized design also exhibited smoother stress gradients and enhanced load distribution, which are essential for durability and safety. The final material configuration favored a hybrid combination of lightweight aluminum alloys and high-strength steel, balancing stiffness, weight, and fatigue resistance. This selection not only achieved superior mechanical performance but also satisfied manufacturability and cost constraints, making it suitable for both mass-market and high-performance applications.

DISCUSSION

The results of this study highlight the transformative impact of smart algorithm applications in the domains of mechanical engineering and physical sciences. Through the development and deployment of a hybrid computational framework integrating artificial neural networks (ANNs), non-dominated sorting genetic algorithms (NSGA-II), Bayesian optimization, and physics-informed neural networks (PINNs) the research has achieved substantial advancements in multi-objective design optimization, predictive modeling, and data-driven engineering decision-making. These outcomes demonstrate the feasibility and effectiveness of replacing or complementing traditional design methodologies with intelligent, algorithmically driven processes that offer greater speed, flexibility, and adaptability.

The proposed optimization framework has proven capable of simultaneously minimizing structural mass and material cost while enhancing fatigue life and mechanical performance. This outcome supports the central hypothesis of the study: that smart algorithms, when properly configured and integrated, can outperform conventional simulation and design workflows in both accuracy and computational efficiency. One of the most notable achievements is the significant reduction in computational time, made possible through the use of surrogate models and adaptive sampling. These components allow for the rapid assessment of thousands of design configurations without requiring full finite element simulations for each iteration enabling practical, high-fidelity optimization even in time-sensitive engineering environments.

The effectiveness of ANNs as surrogate models was evident in their ability to capture complex nonlinear relationships between design inputs and performance outputs with high predictive accuracy. This finding is consistent with prior studies such as (Nematov & Hojamberdiev, 2025; Yang et al., 2023), which similarly demonstrated the utility of machine learning in mechanical diagnostics and materials discovery. Furthermore, the integration of PINNs within the learning framework ensured that physical laws and boundary conditions were respected, thereby enhancing the interpretability and reliability of predictions. This synergy between data-driven and physics-informed modeling addresses a critical limitation of black-box AI methods and aligns with the growing demand for explainable and trustworthy computational tools in engineering practice.

The optimized results, especially those exhibiting Pareto efficiency across the competing objectives of mass, fatigue life, and cost, are particularly relevant for high-performance applications. These include electric vehicle components, aerospace structures, and biomedical implants, where trade-offs between weight reduction, durability, and material cost are pivotal. The observed improvements in natural frequency and reductions in vibration transmissibility further validate the suitability of the proposed designs for use in dynamic environments—an area where traditional static optimization approaches often fall short.

Comparison with Related Work

This research contributes to the growing literature on smart algorithms in engineering design by extending the application of intelligent systems into areas traditionally dominated by deterministic models and manual processes. For instance, the work by Park et al. (2020)on reinforcement learning in HVAC energy control demonstrated the potential of AI in operational optimization. However, this study broadens the scope by applying similar intelligent principles to structural mechanics, with an emphasis on enhancing mechanical robustness and multi-objective trade-off analysis.

In materials science, Li et al. (2022) employed generative adversarial networks (GANs) for the design of high-entropy alloys, illustrating the role of AI in accelerating discovery. The present study complements this approach by directly integrating material selection into the mechanical optimization process, using aluminum–steel hybrids as a

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proof of concept. This integration illustrates the versatility of the proposed framework in uniting disparate engineering domains within a single optimization cycle. Moreover, the framework extends the work of Xu et al. (2025), who proposed a multi-objective optimization strategy for mechanical-material co-design. While their work focused on performance tuning using evolutionary techniques, this study advances the state of the art by incorporating PINNs and Bayesian learning, thereby improving both the convergence speed and the physical interpretability of the solution space. These enhancements are particularly important for applications where both performance and regulatory compliance are critical.

Limitations and Threats to Validity

Despite the promising outcomes, the study is subject to several limitations. A primary constraint lies in the reliance on simulated data for the training of surrogate models. While these models demonstrated high accuracy during validation, real-world experimental testing remains essential to confirm their robustness in operational settings. Material properties such as long-term fatigue behavior, corrosion resistance, and environmental degradation were not fully modeled, which could impact the validity of performance predictions under realistic service conditions. Another limitation involves the assumption of quasi-static loading conditions within the optimization framework. Although this approach simplifies model formulation and computational requirements, it may not fully capture the complexity of dynamic or stochastic loading environments encountered in fields such as aerospace, robotics, or off-road vehicle systems. Future work should incorporate uncertainty quantification, probabilistic modeling, and time-dependent simulations to address these issues more comprehensively.

The framework also depends on expert-defined design variables and constraints, which, while necessary for problem definition, may limit the discovery of novel design solutions. Autonomous feature discovery through unsupervised learning or generative modeling could be explored in future implementations to expand the solution space beyond conventional assumptions. Lastly, although the current implementation performed well for mid-size engineering problems, scaling the methodology to extremely high-dimensional systems may introduce new computational challenges. Large-scale applications may require distributed computing infrastructure or more sophisticated dimensionality reduction and feature selection techniques to maintain feasibility and performance.

CONCLUSION

This study presents a comprehensive framework that integrates smart algorithmic techniques—namely artificial neural networks (ANNs), genetic algorithms (GAs), Bayesian optimization, and physics-informed neural networks (PINNs) to address complex multi-objective optimization problems in mechanical engineering and physical sciences. By unifying data-driven learning with physical constraints, the proposed methodology effectively bridges the gap between predictive modeling and physically accurate engineering design, offering a scalable and interpretable solution to system-level and material-level optimization challenges. The research contributes significantly to the field by demonstrating that smart algorithms can be deployed not merely as auxiliary tools but as central components of the engineering design workflow. The framework enabled substantial reductions in structural mass and material cost, while simultaneously enhancing fatigue performance and compliance with mechanical constraints. The surrogate models embedded within the optimization loop provided accurate predictions at a fraction of the computational cost required by full finite element analysis (FEA), thereby facilitating faster design iterations and expanding the practical feasibility of high-fidelity design optimization. This work also addressed the research questions posed at the outset. First, the study confirmed that smart algorithms can significantly enhance mechanical and material optimization by reducing computation time and improving solution quality. Second, it demonstrated that the integration of data-driven and physics-informed methods provides a powerful balance between efficiency and interpretability. Third, the research showed that a unified cross-domain optimization approach is feasible and effective, thus enabling co-optimization of system behavior and material properties in a single computational framework. Furthermore, the findings support the broader thesis that artificial intelligence, when thoughtfully integrated with engineering knowledge, can elevate the scope and effectiveness of engineering innovation. The application of this framework to the optimization of an electric vehicle suspension system offers a strong case for its applicability in other high-performance engineering sectors, such as aerospace, energy systems, and biomedical design. This study provides a forward-looking blueprint for the use of smart algorithms in advanced mechanical and physical system design. Future research may extend this work by incorporating real-time data, stochastic load modeling, and unsupervised learning for autonomous feature discovery. As the demands on engineering design grow more complex, the integration of AI and engineering will be not only advantageous but essential to achieving innovation at scale.

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