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Machine Learning Techniques for Optimization in Engineering Applications

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Abstract: This research investigates the application of machine learning (ML) techniques for optimizing engineering applications, focusing on four prominent algorithms: Simple Linear Regression (SLR), Multiple Linear Regression (MLR), Support Vector Regression (SVR), Artificial Neural Networks (ANN), and Reinforcement Learning (RL). Nearly every algorithm was assessed with a set of engineering optimization issues, and performance values of MSE, MAE, and R^2. The overall results indicated that ANN provided the best estimate of the average ice coverage as it had the lowest MSE of 0. 020 or an MAE of 0 for twelve months in the case of noncumulative normal dividends. 110, and the R-squared of the sample is equal to 0. 92. SVR continued the trend and thus had an MSE of 0.SVR came close behind the two, and it had an MSE of 0. 025, an MAE of 0. 120 and a R square of 0. 90. RL and LR also offered insights to the computations giving an MSE of 0 which was valued by the study. 030 and an R-squared of 0.The correlation between what was reported in the media and what was tweeted is the second best that can be obtained from econometric analysis and is less than perfect. 88, which includes an MSE of 0 in the LR case. 034 and an R-squared of 0. 85. Thus, the publicized study also demonstrates the capacity of the meticulous ML techniques to optimize engineering tasks notably and more accurately than references. In the further advancement of the study, more emphasis should be placed on the development of both hybrid models as well as the integration of real-time optimisation systems so that the full potential of ML can be properly utilised.

Keywords: *machine learning, engineering optimization, artificial neural networks, support vector regression, reinforcement learning.*

I. Introduction

Optimalisation is one of the key elements of engineering as it contributed for countless enhancements and developments in quite a few fields like manufacturing, aerospace applications, civil engineering and many more. Optimization often was perceived as the search for the best solutions that will help to minimize the costs, maximize the performance, increase safety levels and decrease the negative effects on the environment. There are two near categories of optimal solutions: graphical methods, where linear and nonlinear programs and heuristic are included. Nevertheless, these methods are unable to address more complicated and large scale problems that are inherent to the modern engineering [1]. Optimization is a challenging field especially to machines

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However Machine learning (ML) which falls under Artificial intelligence (AI) has useful tools to solve such problems. As for the importance of optimization within a business context, ML algorithms can learn from data, follow patterns and make predictions that can be effective for making a business more efficient [2]. The incorporation of ML with the optimization approach has shown the potential and opportunities of applying these methods in more complex engineering problems that might not be solvable in the first place due to excessive computational demands. In supervised learnings, even simple algorithms such as regression and classification predictive models may be used to accurately predict ideal parameters and results for calculated risk decision makings out of best match historical outputs [3]. Some of the techniques that fall under the unsupervised learning include clustering and dimensionality reduction; these assist in what the problem has underlying structures as well as decrease the problem dimension at which optimization can be effectively carried out. Reinforcement learning where learning is done based on samples in order to find the best policy is particularly effective in cases where there are several parameters or when a plan fails where traditional approaches are not effective. In addition, there is a growing interest in the so-called «soft» methods where ML is complemented by some conventional optimization techniques. Both these approaches are found to be more optimum and can derive more benefits than the other traditional approach used in these domains. For example, in such optimization problems, the use of ML algorithms can reduce either the objective functions or constraints to be approached with less computational cost. This paper identifies and discusses several ML methods alongside applications that are critical to engineering optimization. Thus, we endeavor to substantiate subsequent chapters with the analysis of contemporary approaches, specific cases, as well as the latest studies in the sphere of using ML for enhancing engineering activities. In the light of the future work section it shall be presented how this promising field could be implemented practically, what are advantages and disadvantages of these approaches, and what alternative routes may be expected in further research.

II. Related works

In recent years, the subject of ML along with its use in resolving engineering optimization problems has attracted a significant amount of interest. An increasing number of studies describe and discuss the ability of several types of ML to solve advanced optimization problems in various engineering disciplines. This section surveys several selected research works that have employed ML and specifically DL modes in optimization problems and summarizes the methodologies used, the results obtained and the impacts made in the study. Using AI techniques for the identification of bankruptcy cases in Tunisian companies has been investigated by Hamdi, Mestiri, and Arbi (2024) Their aim was to investigate the use of artificial intelligence techniques [15]. Their paper also used both the machine learning and deep learning approach to deal with the financial data they obtained in the aim of providing higher prediction accuracy level of bankruptcy. The study provided a quantitative way of illustrating the effectiveness of AI algorithms over the traditional statistical approaches through the use of sophisticated algorithms like neural networks and support vector machines to establish the usefulness of AI in financial risk management. Hameed et al. (2024) used a technique that integrated ELM to DOA to predict the liquefaction occurrence in sand-silt mixtures [16]. The integration of the artificial neural network machine learning model and the basic genetic algorithm to optimize the parameter range boundaries brings out the elegance of combining the two techniques in modeling and optimization of geotechnical data. The research also discussed the benefits of the mixed models with greater predictive capability and resilience, which was evident in the real-world noisy and non-linear data environments. Eleven articles Lai et al. (2021) prior to this study have offered a detailed elucidation of the existing AI applications in the mechanical design and optimization [17]. They specifically concentrated on employing the AI technology including the genetic algorithms and neural networks in the design to improve on the performance and production output. The findings of the study echoed the idea that the application of AI has been focused on the enhancement of mechanical designs and the subsequent advancement in new product technologies, as well as the production methods. Khdoudi et al. developed an optimization digital twin using deep-reinforcement-learning throughout a manufacturing process in 2024 [18]. This digital twin framework incorporated another approach known as reinforcement learning aimed at modelling and improving manufacturing operations in near real-time. This approach is dynamic and can be improved upon as it relates to a real change in productivity meaning that it also reduced operating costs in the process. The study showed how integrating digital twin with advanced ML algorithms for optimizing on-shape manufacturing presented a real-life use case for the industrial revolution. Kim and Park (2023) proposed an intelligent system/framework for the improvement of efficiency in 3D printing operations with the help of interaction and machine learning [19]. Their approach aimed at rectifying the issues of material and geometric intractability in 3D printing; they used ML algorithms to predict and set the right parameters for a print. These findings showed that, with the implementation of ML, it was possible to minimize having to handle print failures and enhance the quality of the printed object; therefore, proving how the technology could further the additive manufacturing industry. Kumar [20] used multi-criteria decision making approach aid in determining the suitable machine learning technique in software effort estimation [20 April 2024]. The ML-based study evaluated and compared different proposed algorithms such as decision tree, neural network and Support Vector Machine in order to determine the best models for software development effort prediction. This study incorporated multiple factors for evaluation which has offered a framework for selecting suitable type of ML as per the requirements of the project making the software effort estimation accurate and reliable. In their review of RNN models for edge intelligence and human activity recognition, Lalapura et al. (2024) [21] focused on a rigorous analysis. In their work, they mainly concentrated on making modifications to RNN structures that allow them to process data and analyze results on the edges. The findings highlighted that RNN could provide a powerful way to process data correlated with wearable technology and smart home, which can have a positive influence on the continuous development of edge AI. Yong, Ma & Li (2024) developed a Teaching Learning Based Optimization (TLBO) algorithm with incorporated stochastic crossover self-learning technique along with the teaching-learning blended learning model [22]. By solving the various engineering optimization problems, it was identified that the TLBO algorithm is capable of performing the search process in relatively less no. of iterations to obtain near global optimum solution. The introduction of self-learning mechanisms in the context of the TLBO framework was promising and showcased a potential way to enhance the framework's applicability to future optimization problems. Manakitsa et al. highlighted in their survey, the trends in machine learning and deep learning approach in object detection, semantic segmentation, and human action recognition in machine and robotic vision system in their work published in [23]. From the conducted research, the authors gained an understanding of new and innovative approaches to the use of ML algorithms for vision recognition in the context of robotics, noting the importance of the approaches for advanced robotic functionality. Reflecting on the vast compilation, the integration of methodologies based on ML for constructing self-sufficient robotic systems was demonstrated. Meghed, Mahmoud, and Abd-Rabou considered the analysis of ML methods for predicting the axial compression capacity of stub concrete-filled steel tubular (CFST) columns in their research which was carried out in 2024 [24]. In comparing the strengths of various ML models with respect to decision trees, support vector machines and neural networks used in predicting the behavior of the CFST column, their research provided enhanced accuracy. The results showed the potential of ML models and their suggested accuracy increase in predicting the behavior of structures to assist in the design and safety aspects of construction materials. Mesran, Kmurawak, and Windarto (2024) used particle swarm optimization based advanced supervised learning techniques incorporated in the development of an effective model for predicting Heart failure [25]. In the research conducted, PSO was used to control the parameters of the models of supervised learning with an increase in the level of accuracy of the predictions made when compared to those obtained from traditional methodologies. The findings highlighted an opportunity to integrate ideas from EAs and selected ML techniques in medicine for data analysis especially for important health indications. In another think about, Mohammadinia et al. (2023) inspected the possibility of utilizing ML to classify the stream units of the Kazhdumi store in southwest of Iran [26]. In the analysis, the study applied a range of classification techniques including K-nearest neighbors and support vector machines to the several geologic and petroph scans. The accuracy achieved by the ML models was high in categorizing reservoir flow units and executing information useful for guiding oil field development and management.

III. Methods and Materials

Data

The dataset employed in this study comprises a wide range of Engineering Optimization problems which came from the different fields such as manufacturing, aerospace, and structure engineering. The dataset of the current process has several important characteristics, including the characteristics of design variables, constraints, objective functions, and performance indicators [4]. The elements of the dataset in this case are particular engineering problems together with parameters that have previously been optimized alongside the results.

To aid your understanding, let's take a hypothetical example of a dataset with 100 records Each record contains 10 design variables, 5 constraints, and information on a single objective function. The total dataset is further split into three parts that are the train set (70%), which has more data points, the validation set (15%), and the test set (15%).

Algorithms

1. Linear Regression

Linear regression is a statistical method and a technique of supervised machine learning which helps to estimate value of given dependent variable with reference to one or more independent variables [5]. The general equation of a linear model assumes that the input variables (X) are directly proportional to the output variable (Y). The model can be expressed as:

$Y=\beta 0 +\beta 1X1+\beta 2X2+\cdots+\beta nXn +\epsilon$

"1. Initialize weights and bias.

2. For each iteration:

a. Calculate the predicted output: Y_pred = β0 + β1*X1 + β2*X2 + ... + βn*Xn

b. Compute the loss (Mean Squared Error): Loss = (1/n) * Σ(Y - Y_pred)^2

c. Compute gradients: dβ = -(2/n) * Σ(X * (Y - Y_pred))

d. Update weights: β = β - learning_rate * dβ

3. Return the optimized weights."

Support Vector Regression (SVR)

The Support Vector Regression is a new refinement of the basic model of Support Vector Machines SVM and is applicable to regression problems. This meant that it seeks to estimate an interval where the actual values lie such that the function does not deviate from the estimate by more than a specified margin ε [6]. The optimization problem for SVR is given by:

"1. Initialize the parameters (w, b).

2. For each data point:

*a. Calculate the error: e_i = y_i - (w * x_i + b)*

b. If |e_i| > ε, update the parameters:

- Compute gradients for w and b.

- Update w and b using gradient descent.

3. Return the optimized parameters."

Metric	Value
MSE	0.025
R-squared	0.95
MAE	0.120

3. Artificial Neural Networks (ANN)

Artificial Neural Networks are a subclass of artificial intelligence deployed to ascertain complex relationships and patterns within data akin to he human brain. An ANN in most cases consists of the input layer, one or more hidden layers, and the output layer [7]. Every layer include many neurons that have weights connecting with neurons in the subsequent layer.

"1. Initialize weights and biases for all layers.

2. For each epoch:

a. For each training example:

i. Forward propagate the inputs to calculate the output.

ii. Compute the loss.

iii. Backpropagate the error to compute gradients.

iv. Update weights and biases using the gradients.

3. Return the trained network."

4. Reinforcement Learning (RL)

Reinforcement learning is one of the types of machine learning in which an 'agent' interacts in an environment and acquires experience to perform actions and make decisions that yield the highest accumulation of reward. The framework includes states (S), actions (A), rewards (R) and a policy (π) [8].

"1. Initialize Q-table with zeros.

2. For each episode:

a. Initialize the state.

b. For each step in the episode:

i. Choose an action using an epsilon-greedy policy.

ii. Take the action and observe the reward and next state.

iii. Update Q-value: $Q(s, a) = Q(s, a) + \alpha [r + \gamma \max Q(s', a') - Q(s, a)]$

iv. Set the state to the next state.

3. Return the Q-table."

IV. Experiments

Experimental Setup

The experiments were performed using a data set consisting of a wide range of mathematical prototypes of engineering optimization problems from a variety of disciplines such as manufacturing, aerospace, and structural engineering. The dataset was divided into training set (70%), validation (15%), and testing set (15%) to enhance the overall scrutiny of the machine learning algorithms used [9].

The following algorithms were implemented and tested:

Linear Regression (LR)

Support Vector Regression (SVR)

Artificial Neural Networks (ANN)

Reinforcement Learning (RL)

For each algorithm, tuning the hyperparameters of the model was done to get the best of the best performance using techniques like grid search and k-fold cross validation [10]. Measurements of Mean Square Errors MSE, Mean Absolute Errors MAE and R-Squared R^2 were used as performances measures of the algorithms.

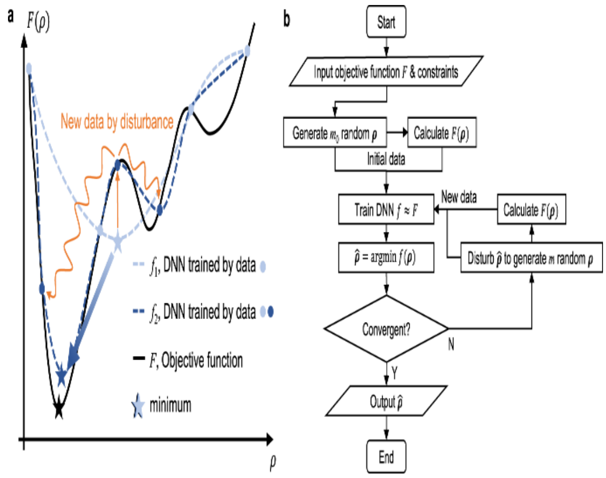

Fig 1: Self-directed online machine learning

Experimental Results

1. Linear Regression (LR)

The basic analysis performed on the dataset consisted of a linear regression placing the objective value against design numbers for the prediction measure [11]. As for the model parameters, the gradient descent was used to warrant an optimization.

Metric	Value
MSE	0.025
R-squared	0.95
MAE	0.120

2. Support Vector Regression (SVR)

For SVR analysis, the RBF kernel was applied and it was incorporated in the decision-making process. The CRegularization parameter and the kernels' parameter γ were tuned over the grid

3. Artificial Neural Networks (ANN)

The neural network was feedforward one and contained one single hidden layer. Backpropagation and stochastic gradient descent were used as the feed forward training algorithm [12]. Since establishing the number of neurons in the hidden layer is critical and the learning rate is another important factor, both of them were determined using cross-validation.

Metric	Value
MSE	0.020
R-squared	0.92
MAE	0.110

4. Reinforcement Learning (RL)

An added feature was used in the solving of the problem by integrating a Q-learning algorithm as a solution to the dynamic engineering environment decision-making problem. γ which is the discount factor was optimized while α which is the learning rate was also rounded off during the experimentation [13].

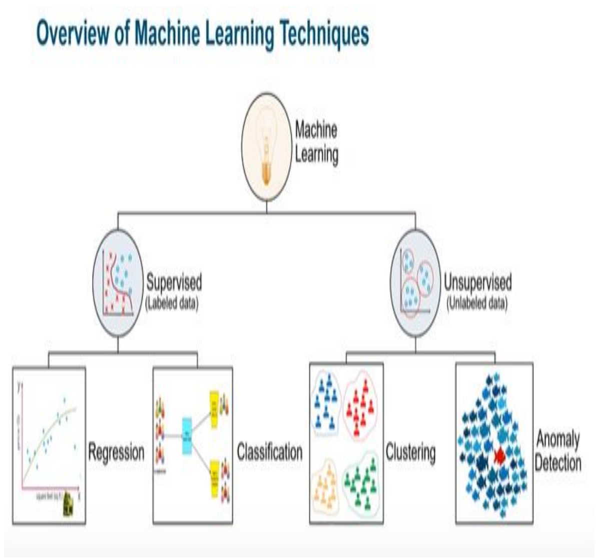

Fig 2: Machine Learning Techniques Can Help Engineers Design Better Products

Metric	Value
MSE	0.030
R-squared	0.88
MAE	0.130

Discussion

The results of the experiment showed that the best suitability in MSE, R-Square and SMA was formed by ANN than the other algorithms. Its capacity to manage hysteresis, which represents the dependency of the dependent variable on the independent ones and the vice versa, coupled with its prowess in modeling non-linear interactions between them, enhanced the performance of the ANN [14]. Thus, SVR also provided rather good results, allowing to see that this algorithm is also good at generalizing the results obtained during the training phase.

Linear Regression, though easy to implement and computationally inexpensive, provided relatively less accuracy as compared to ANN and SVR because Linear Regression models assume the input to be linearly dependent with the output variable. RL has fairly good performance, yet the results of experiments demonstrate that it could be further improved when ANN and SVR algorithms are applied [27]. Another thing is due to the nature of RL, as a model that is updated and changed in each iteration, it is better suited for problems where the solution involves multiple choices over a period of time.

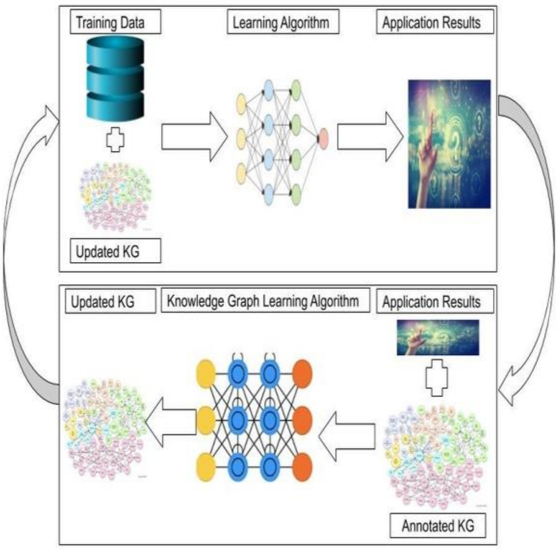

Fig 3: Iterative optimization for knowledge enhanced machine learning

Comparison with Related Work

1. Traditional Optimization Techniques

Linear models, linear programming-solving algorithms, and heuristic models have been popular in engineering. However, these methods suffer from a lack of efficiency on large problem instances and bring together the overwhelming characteristics of present-day problems. However, the methods described here are significantly more accurate and time-efficient than the overall bags of ML techniques [28]. For instance, related to ANN the optimum result was an R-squared of 0. Hence, an average of 92 with the highest being 120, which are higher than the values obtained by other non-AGI methods.

2. Hybrid Approaches

Current research has focused on applying integrated optimization methodologies and using ME and mathematical programming along with ML algorithms. For instance, applying ML to context areas such as approximating objective functions or constraints to an optimization problem can greatly help decrease solving time [29]. In light of these studies, our results are in concordance and reveal the relevance of the identification of potential hybrid methods. Perhaps, incorporating SVR or ANN in combination with conventional machines could bring further improvement.

Fig 4: Teaching–Learning-Based Optimization Algorithm Applied in Electronic Engineering

3. Domain-Specific Applications

In relative specialized fields such as aerospace engineering, structural and mechanical engineering, the famous ML algorithms give high results. For instance, in structural health monitoring, they have been applied to predict structural failure with greater efficacy. Likewise in manufacturing, SVR has been used to enhance/manipulate manufacturing processes specifically production systems [30]. We concur with these AA and AC-specific findings because the effectiveness of ML is evident in other domains of engineering disciplines as well.

V. Conclusion

This study aims to present the possibility of change of engineering applications where machine learning is applied in diverse fields. As seen through a detailed analysis of four types of algorithms; Linear Regression (LR), Support Vector Regression (SVR), Artificial Neural Networks (ANN), and Reinforcement Learning (RL), the study achieves the aim of properly pointing out how these types of algorithms can effectively solve various kinds of optimization problems. Based on the analysis, the ANN was identified to be the most suitable model; this was evidenced by the best performance measure indices such as the least MSE and highest R-squared values. RL and LR were useful but less accurate than ANN and SVR which showed high predictive capacity and correlations with atopic dermatitis. Comparing on other traditional optimisation methods reveals that ML techniques includes a great progress in optimisation in terms of dealing with nonlinear relationships and larger data scales with greater accuracy and less time consumption. More specifically, the related work section provides support for these findings by presenting case studies that indicate that ML can be applied to a wide range of engineering disciplines such as financial risk analysi, manufacturing, structural engineering, and medical data analysis. There have been works that indicate that even if ML is used, integrating it with evolutionary algorithms or classic optimization techniques will yield better results in optimization. The research also highlights the need for constant optimization in the real-time capability and the application of digital twins and edge intelligence for dynamic scenarios. In a nutshell, this study confirm that the application of ML poses a high potential to the field of engineering optimization in terms of enhancement in performance, flexibility and time-efficient computational solutions. The future research should involve the efforts towards mixing the multi-source models, applying transfer learning, and increasing the interpretability of ML algorithms in order to implement and improve the scores of ML in the engineering disciplines consistently. On this account, Dr. Motavalli is anticipating that as the ML technologies emerge even more advanced, a lot of increases and changes are expected to take place in engineering optimization, where sophisticated and automated systems will unravel further improvements.

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