International Journal of Multiphysics
Volume 18, No. 2, 2024
ISSN: 1750-9548

# Application of Artificial Intelligence in Industrial Design: An Exploration from Concept to Practice

**Wu Jie**
Anyang Institute of Technology , School of Art and Design，HeNan 455000，China
Email：20160735@ayit.edu.cn

**Abstract**

Designing industrial products is a complicated process that requires maximizing a number of factors to get the required level of quality and performance. The model's effectiveness may differ on the intricacy and unpredictability of the industrial design challenge. This study introduces a novel Firefly Algorithm Fine-Tuned Random Forest (FA-FRF) model to demonstrate the efficacy of optimizing industrial product design processes. The research makes use of an extensive dataset that includes several industrial product design criteria, such as capacity, material composition, production procedures, and market segmentation. Min-max normalization is one of the data pre-processing stages applied to normalize the characteristics in a given range. The process of feature extraction uses Independent Component Analysis (ICA), which attempts to locate and extract the most pertinent characteristics from the information. Based on the suggested methodology, this study is carried out using the Python program and performance is examined in terms of RMSE (0.0490), MAE (0.0320), MSE (0.0020), MAPE (3.4137), and SMAPE (3.9871) measures. Designers and technicians may optimize design outputs and decision-making in industrial settings with the help of the FA-FRF model, which delivers the enhanced quality and performance.

**Keywords:** industrial, product design, Firefly Algorithm Fine-Tuned Random Forest (FA-FRF), Independent Component Analysis (ICA)

## 1. Introduction

The worldwide development of production imparted rise to the industry periods, while the extensive use of the Internet brought about the communication generation. Artificial Intelligence (AI) is the use of machines to perform dangerous or sophisticated tasks in place of humans, to assist people in dealing with problems, and to develop responses that are similar or stronger than human perception structures. Therefore it launched in the era of large-scale design. Conceptual learning on intelligent product design has consistently drawn interest from both domestic and international audiences due to the AI industry's rapid growth[1]. The issues that need to be resolved include how to conduct intelligent product design efficiently and the particular design challenges intelligent products encounter. Industrial design can become more standardized through the use of AI, which can handle extremely challenging calculation problems in addition to providing designers with new creative ideas. Competent products are crucial design elements in the Creative period, where design is unpredictable[2].

The level of ambiguity in design escalates with the variety of intelligent products. Intelligent product procedure design is a sophisticated decision-making approach that requires extensive experience and specialized understanding[3]. The design of the competent products has evolved from establishing technique substances to building them, due in part to the difficulty and design uncertainty of the product. It has produced a change problem solving techniques from the multidimensional adaptive response approach instead of the conventional single linear response approach. Because of this, the design issues associated with AI-based products require methodical, creative solutions [4].

A component of the product's effort and design unpredictability can be attributed to the evolution of intelligent product design from establishing technique components to producing them. The traditional single linear solution path has been replaced by a multidimensional dynamic solution approach in problem-solving methodologies[5]. This means that the design problems arise with AI-based products need to be solved in a rigorous and creative way. Specialists construct intelligence that is equivalent to human intelligence, translate human intelligence operations into methods, and use this intelligence to process and evaluate data in particular disciplines[6]. As human civilization progresses, machine manufacturing leads to the production of industry, it is the effect of fusing innovation, knowledge, civilization and industries. A significant characteristic of the modern manufacturing sector is that, in theory, product design determines everything about a product, including its framework, operation, effectiveness, expenses, transportation time, fabrication, sustainability, disposal after elimination, and interaction between the human and machine environments[7].

Industrial product design and AI can work together to bring together the expert knowledge, data analysis and creative design that go into product design. It is produced in a relatively comprehensive design scheme that is used to manufacture products that satisfy specifications[8]. The industrial design and transformation platform is designed and implemented using AI technology. Next is the implementation of the AI-based industrial product design and transformation platform. The construction of the scene-driven intelligent product design procedure includes the administration of requirement mining based on customer situations, the operation of product design based on conceptual locations, and the operation of product confirmation and response based on realistic situations. By using output weights and network forecasting, the system may efficiently and precisely interpret the perceptual terminology used to generate quantitative information that can influence industrial design throughout the product design approach[9, 10].

This study introduces a novel Firefly Algorithm Fine-Tuned Random Forest (FA-FRF) model to demonstrate the efficacy of optimizing industrial product design processes. **Contribution of the study**

- Gathered a product design dataset that includes important aspects such as materials, production processes, market segments, and capacity.
- Data pre-processing methods include min-max normalization to scale characteristics and ICA for feature extraction.
- The study present the FA-FRF model to improve operations for industrial product design management.

Section 2 contains a list of related works. Section 3 presents the technique. Section 4 is mentioned in the results. In Section 5, the conclusion is provided.

## 2. Related works

The ML integrated, design for additive manufacturing(DfMA) architecture was presented in the investigation [11] to build correlations between process and structure properties, which might be useful in additive production design. The findings showed that assuming specified property amounts, the property-structure deep neural network (DNN) methods were substantially more computationally effective in computing design parameter values than traditional alternative models.

To streamline the design method for upcoming machine learning (ML) deployments in manufacturing organizations investigated[12] methodically examined effectively deployed ML systems. The results showed that the theory-based MLmethod regularly depends on a linear approach that required low-dimensional data, such as image recognition.

Aninnovative strategy for product design, management, and marketing mechanized by digital twins was presented in the work [13].Digital twins had great potential for use in product design, management, and marketing because of their remarkablearrangement and engagement, a combinationof physical and virtual products, and other features.

The incorporation of ML into the industrial design process had been examined in the investigation [14]. Building intelligent design technology and utilizing ML techniques to analyze data collected or utilized through product design were two promising ways to enhance these procedures, minimize costs, and establish better aspects.

To produce unique latent object characterization that fascinates distinct product characteristic demands, the method described in [15], employed Deep Learning (DL) methods to identify design patterns unique to product relatives from their essential latent communication. The results that had been given to utilize the benefits of designers by suggesting applicable objects and helping them modify subsequent product versions to satisfy approaching requirements.

The method of industrial design flow tuning that the investigated [16] was an expansive one that combined offline and online ML techniques. Based on experimental findings, SynTunSys (STS) online and offline ML technologies worked together and human designers' insights produced superior outcomes.

An effective, quick, and precise industrial equipment monitoring method was constructed by the [17] on fusing the Internet of Things (IoTs) with AI technologies. The experiment findings demonstrated the degree of applicability of the industrial IoTsplatform built in the investigation using ML and AI technologies.

The MLtechniques in the design development of electromagnetic equipment were examined [18] with specific attention to modern advancements. The distribution of the magnetic field and heating could be predicted more accurately with DL algorithms.

The purpose was to develop classifiers that could forecast a storage operation's picking policy (PP), storage allocation strategy (SAS), material handling system (MHS), and storage technology (ST) to assist the operational design of a warehousing operation [19]. As demonstrated by the investigation's findings, precise forecasting required knowledge of the characteristics of stock-keeping units (SKUs) and the fluctuations in the SKUs' market requirements.

The combination of AI approaches into the circular economy (CE) during the product design phase was explored in the investigation [20]. The investigation's findings pointed to the benefit of using AI methods in CE solutions in the industrial sector.

Implemented characteristics and descriptionthat would consequence the product design and development process (PDDP) through the fourth industrial revolution (IR) and into intelligent design strategy was the intent of the investigation [21]. The investigation offered a foundation for affectionate that might influenced smart design technology and its design-related endeavors by developing these findings.

Aninnovative methodology engaged on the conceptof connected design and operation monitoring was developed in the employment [22].The results indicated that, in assessment to the conventional reinforcement learning joint management, the proposed approach could produce a competent inventory of products that were accessible to be sold because it had a better compassionate of the continuous demand from customers.

The determination of the process[23] was to close the gap by recommending a novel Design Support System (DesSS), which was derived from the Des. It was anticipatedto predict and evaluation machine description data, including machine geometry and design, dependon a difference of input variables. The ML-based DesSS calculated to assist with designing decision-making could offer numerous advantages, including reduced decision-making time, knowledge conservation for the business, man-hour savings, and increased computational efficiency and reliability.

The investigation [24] offered a performance evaluation of six ML techniques and compared ML techniques for cost prediction during the early stages of vehicle wheel design. The investigation's findings demonstrated with an $R^2$ of 0.960, it was feasible to forecast product element costs at the early design stage utilizing seven characteristics that were provided by the product design and production organization.

To enable a suitable absorber design, the investigation that was being discussed requires bridging the distance [25] between the acoustic material properties of porous absorbers and their micro-scale shape. It advanced the idea of customizing materials for individual applications and made the method especially beneficial for material design.

**3. Materials and Methods**

The approach includes a comprehensive dataset analysis that includes multiple design criteria and it is normalized using min-max normalization. Important properties are isolated by ICA feature extraction. The FA-FRF model which combines in this work to improve industrial product design development.Figure 1 shows the overall methodology.

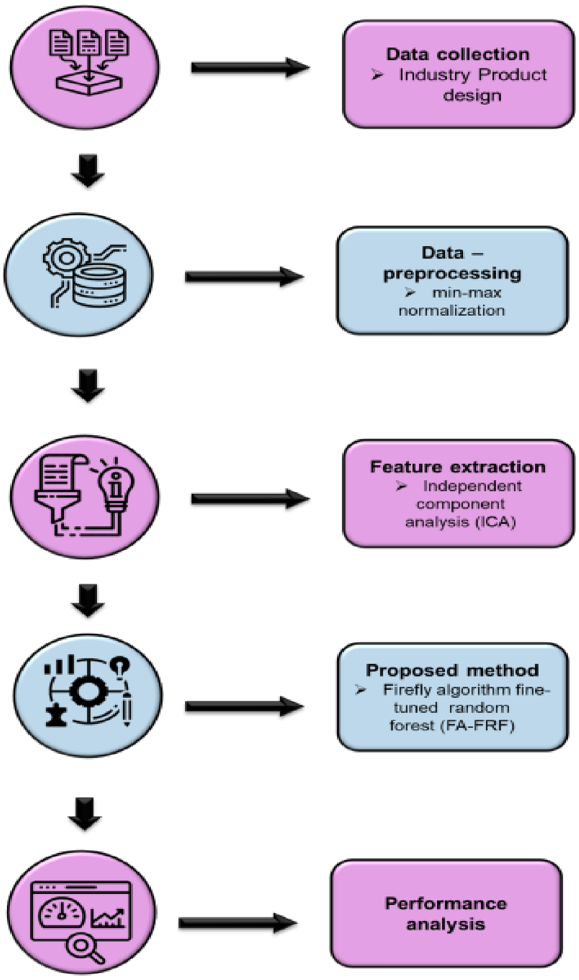


***Figure 1: Overview of methodology***

***3.1 Data collection***

The dataset includes numerous fields for several comfortable office chair types, each distinguished by a distinct Product ID. Recyclable plastic, aluminum, steel, composite fiber, and wood are used to make the chairs. There are differences in weight capacities, from lower to greater assistance. While some chairs have tilt and height adjustments, many might do nothing. The cost of manufacturing varies per unit. Customer satisfaction values range from average to excellent. Sales numbers vary between models. Customer experience and product dependability are reflected in return rates. The chairs are aimed at many market categories, including Industrial, Professional, and Home Office. Based on typical usage, reliability predictions range from short to lengthy lifespans. Higher ratings suggest the stronger environmental behaviors. Environmental impact scoresthe measure sustainability efficiency. Table 1 provides a description of the dataset.

***Table 1: Dataset description***

| **Product ID** | **Material Used** | **Weight Capacity (lbs)** | **Adjustable (Yes/No)** | **Cost to Manufacture ($)** | **Consumer Rating (1-5)** |
|---|---|---|---|---|---|
| 1 | Recycled Plastic | 220 | Yes | 45 | 4.2 |
| 2 | Aluminum | 300 | Yes | 60 | 4.5 |
| 3 | Steel | 350 | No | 40 | 3.8 |
| 4 | Composite Fiber | 250 | Yes | 55 | 4.7 |
| 5 | Wood | 200 | No | 35 | 3.5 |
| **Product ID** | **Number Sold** | **Return Rate (%)** | **Durability (Years)** | **Environmental Impact Score (1-10)** | **Market Segment** |
| 1 | 1500 | 1.2 | 5 | 8 | Home Office |
| 2 | 1200 | 1.0 | 10 | 7 | Professional |
| 3 | 800 | 2.3 | 15 | 5 | Industrial |
| 4 | 1800 | Home Office | 0.9 | 9 | Home Office |
| 5 | 500 | Home Office | 3.1 | 6 | Home Office |

***3.2 Data pre-processing***

It includes eliminating redundant information, managing absent values, standardizing elements, and adjusting data to guarantee reliability and effectiveness throughout the design procedure.

#### *3.2.1 Min-Max Normalization*

The method transfers the characteristics or outputs from one value range to another value range in a linear fashion. Generally stated, the parameters are changed to fall into one of two ranges 0 or -1. Typically, the linear transformation with the formula as follows to accomplish the rescaling.

$$z = \frac{w - \min(w)}{\max(w) - \min(w)} \tag{1}$$

In $w$ which is the collection of observed numbers of $w$ min and max denote the minimum and maximal numbers, respectively. Stated differently the range of $w$ equals$\max(w) - \min(w)$. The fact that each connection in the data is precisely maintained,which makes this normalization technique effective.

### *3.3 Feature extraction*

The procedure aids in comprehending crucial components that enhance the product's usability, appearance, functioning, and manufacturing potential.

#### *3.3.1Independent Component Analysis (ICA)*

To identify hidden components from a sequence of observations or recorded data so that the resources are optimally independent, ICA is a comparatively modern quantitative and computing approach.

From a mathematical perspective, the observed parameters $\mathrm{w(s)} = \mathrm{w_1(s), w_2(s), \ldots, w_m(s)}$are made up of the linear combinations of the initial, completely independent cause $\mathrm{t(s)} = \mathrm{t_1(s), t_2(s), \ldots, t_m(s)}$at time period $s$, stated as

$$\mathrm{w(s)} = Bt(s\ ) \tag{2}$$

Where $B$ is a complete ranking mix vector, in ICA standards, Eq. (2) is frequently expressed as

$$z = Xw \tag{3}$$

Where the independent element is denoted by $z = z_1, z_2, \ldots, z_m$, and the demixing vector is represented by $X = B^{-1}$. The purpose is to predict the independent elements and demixing vector exclusively from the mixed records. Several ICA methods, such as fastICA, Joint Approximate Diagonalization of Eigen matrices (JADE), Infomax, etc., can be used to accomplish this purpose.

According to the ICA assessment standards, the retrieved elements are independent and non-gaussian. One technique to quantify non-gaussianity is to use kurtosis($\beta_1$). The kurtosis values of the Gaussian independent variables (ICs) are 0 for sub-gaussian$\beta_1 \leq 0$and $\beta_1 \geq 0$ for super-gaussian. The definition of the traditional kurtosis measurement is

$$\beta_1 = \frac{\mathrm{F(w-\mu)^4}}{(\mathrm{F(w-\mu)^2})^2} - 3 = \frac{\mu_4}{\sigma^4} - 3 \tag{4}$$

The traditional kurtosis measurements are similarly susceptible to outliers because they are reliant on sample averages. Furthermore, because the standard measurements of kurtosis boost the values of kurtosis to the third and fourth powers, the effect of outliers is significantly magnified to employ an accurate indicator of kurtosis in the ICA quantile kurtosis as an alternative to $\beta_1$to solve the presented problem. The amount of kurtosis is

$$Kurtosis = \frac{(F_7 - F_5) + (F_3 - F_1)}{(F_6 - F_2)} \quad (5)$$

Where $F_j$ represents the $j^{th}$ octile, or $F_j = E^{-1}\left(\frac{j}{8}\right)$. The quantile kurtosis for Gaussian independent elements is 1.23. The quantile estimates of kurtosis have the benefit of not relying on the first or second instant. Hence, it is more reliable than the traditional kurtosis measurement. Because it yields substantially independent elements, ICA is helpful as a dimension-preserving modification in pattern recognition. Moreover, ICA has been applied directly to feature extraction.

### *3.4Optimizing Industrial Product Design*

To maximize efficiency, utility, and attractiveness, industrial product design optimization entails perfecting every element, from functionality to aesthetics. To make a better and more competitive product, one must strike a balance between consumer demands, market trends, technological specifications, and production capability.

#### *3.4.1 FA*

FA was founded on the habits and patterns of F flashing. FA essentially applies these three idealized principles. 1. Because they are unisex, F’s will always be drawn to other fireflies of the same sex. 2. F's luminosity and appeal are inversely correlated, with both decreasing with distance. The less brilliant F will gravitate toward the brighter one when there are two flashing Fs. If F is stronger than then it wasn't present, it will migrate at random. 3. The landscape of the goal function controls an F's luminosity.

The luminosity of a maximizing challenge can be expressed as a simple function of the ultimate function number. It must specify the fluctuations in light intensity and attraction since there is an impact on the FA's behavior. To keep things simple, we can constantly assume that a F's luminosity, which is linked to the encoded value function, determines how attractive it is. A F's intensity $J$at a given position $w$ can be determined using the simplest case for maximal optimization issues $\mathrm{J(w)} \propto \mathrm{e(w)}$.

But $\beta$ attraction is approximate; one should estimate it by looking at it or by comparing to the other F. It will change depending on the distance $\mathrm{q_{ij}}$between F$j$ and F$i$. As a result, we can describe a F's attractions $\beta$ by;

$$\beta = \beta_0 f^{-\gamma q^2} \quad (6)$$

The attraction at $q = 0$ is represented by $\beta_0$. Indeed, the attraction decreases dramatically from $\beta = \beta_0 f^{-\gamma q^2}$along the characteristic distance $\Gamma = \frac{1}{\sqrt{\gamma}}$defined by equation (6). The Cartesian distance, denoted as$\mathrm{q_{ji}} = \left\|w_j - w_i\right\|$, calculates the distance between exactly pair F, $j$ and $i$, at $\mathrm{w_j}$ and $\mathrm{w_i}$, accordingly.It is important to note that there are other distances $q$ besides the Euclidean distance. The distance $q$ can be any metric that can accurately describe the quantities of concern in the optimization issue. Depending on the nature of the topic we are interested in, we can define different distances$q$ in the $n$-dimensional hyperspace.

The motion of F$j$ is drawn to another equally intriguing (brighter) F$i$ for every given pair of fireflies, $\mathrm{w_j}$ and$\mathrm{w_i}$.

$$w_j^{s+1} = w_j^s + \beta_0 f^{-\gamma q_{ji}^2}\left(w_j^s - w_i^s\right) + \alpha_s \epsilon_j^s \quad (7)$$

Where the attraction is the cause of the second component, the third component is randomization, where $\epsilon_j^s$is a vector of random numbers selected from a regular or Gaussian transportation, and $\alpha_s$ is the randomization variable. By evaluating and modifying each pair of Fs during each iteration cycle, the position of the insects can be sequential manner.

Although we discovered that it is preferable to employ a time-dependent $\alpha_s$ so that randomization can be substantially decreased as repetitions continue, for the majority of executions, we can choose $\beta_0 = 1$and

$\alpha_s = P(1)$. It is important to note that (7) is a biased selection in favor of the brighter F. It turns into a basic random walk if $\beta_0 = 0$. Moreover, it is simple to generalize the randomization component in comparison with different distributions,

The attractiveness fluctuation is characterized by the variable $\gamma$, the behavior of the FA algorithm and the rate of convergence depend critically on its value. The specific distance $\Gamma$ of the mechanism to be optimized determines $\gamma = P(1)$in practice, even though in principle$\gamma \epsilon [0, \infty]$. Therefore, it usually fluctuates between $10^{-5}$ and $10^{5}$ for most applications. Using modified, vectorised settings, we take into account the scale differences of every issue.

$$\propto = 0.01K, \quad \gamma = \frac{0.5}{K^2} \tag{8}$$

Where $V_a$ and $K_a$ are the upper and lower bounds of $w$ accordingly and $K = (V_a - K_a)$.Here, the parameter 0.01 was determined using a parametric investigation to ensure that the randomized walks were not overly aggressive.

***3.4.2 FRF***

The section presents the Feature weighting (FW) approach for subspace sampling (SS), followed by the presentation of a tree selection technique. An innovative, fine-tuned RF algorithm is suggested by combining these two techniques.

- FW Method

The FW approach for SS in RF will be explained in depth in the subsection. Imagine the characteristic space $\{B_1, B_2, \dots, B_N\}$in $M$-dimensions. We demonstrate to calculate each featurein the space's weights, which are $\{x_1, x_2, \dots, x_N\}$. Each decision tree in the RF is grown using an improved method that makes use of these weights.

- FW Computation

Using each input feature$B$ correlation to the class feature$Z$ as an indicator of informativeness, we compute the FW. The presence of a big weight implies a correlation between the values of feature$B$ and the class labels of objects in the training data. Consequently, $B$ can provide valuable insights into object class labels and possesses significant predictive power for class labels of newly discovered objects. It is only applicable to data with two classes because Amaratunga utilized a two-sample t-test as the FW. We suggests a utilizing chi-square techniques to calculate FRF to overcome multi-class issues.

Considering the class feature $Z$, which has q different values or classes represented as$z_i$(for $i = 1, \dots, r$). When the feature $B$ can accept $o$ values represented by$b_j = $ (for $j = 1, \dots, o$). A supervised discretization approach is used to discretize $B$ if it is quantitative. Let $C$ be a set of data samples that make up a data set. $\sum_{i=1}^{r}\sum_{j=1}^{o}\lambda_{ji}$ is the number of samples in $C$ where $Z = z_i$and $B = b_j$. These $\lambda_{ji}$all form $B$ and $Z$. The chi-square statistic-dependent correlation is calculated as follows given the class feature $Z$ of a data set $C$ and the contingency of characteristic $B$.

$$corr(B, Z) = \sum_{j=1}^{o}\sum_{i=1}^{r}\frac{(\lambda_{ji} - s_{ji})^2}{s_{ji}} \tag{9}$$

Where $s_{ji}$ is the predicted frequency that can be calculated, and $\lambda_{ji}$ is the observed probability provided in the contingency matrix.

$$s_{ji} = \frac{\sum_{i=1}^{r}\lambda_{ji} \times \sum_{i=1}^{o}\lambda_{ji}}{\sum_{i=1}^{r}\sum_{j=1}^{o}\lambda_{ji}} \tag{10}$$

A feature is given greater weight and is considered more informative when compared to a class feature $Z$ if its $corr(B, Z)$ measurement is greater.

- The Normalized Weights

FW are normalized for feature SS in the application. Assuming that for each $j = 1, \ldots\ldots, M$, the correlation between a feature $B_j$ and the class label feature $Z$ is $corr\ (B_j\ Z)$.

$$x_j = \frac{\sqrt{corr(b_j, Z)}}{\sum_{j=1}^{M}\sqrt{corr(b_j, Z)}} \qquad (11)$$

One typical smoothing technique is to get the square root of the correlation. The normalized weight $x_j$ gauges how informative a feature $B_j$ is in comparison. When constructing our algorithm, this weight information will be employed in characteristic SS.

### *3.5 Firefly Algorithm Fine-Tuned Random Forest (FA-FRF)*

The hybrid approach leverages the finest features of both algorithms to tackle difficult design problems, maximize efficiency, and expedite the product development cycle. The FA solves optimization concerns by taking influence from the natural patterns of fireflies' blinking. It is useful for addressing nonlinear and multimodal optimization assignments, which makes a suitable fit for industrial situations where design parameter optimization is required. This approach can be used to improve the Random Forest model's capacity to adapt from data, produce precise predictions, and provide insightful information for product designers. For industrial product design applications, this hybrid method has various benefits. It allows for the quick exploration of design possibilities, the identification of ideal solutions and data-driven decision-making by combining effective optimization with strong predictive modeling. Furthermore, the incorporation of AI algorithms, such as the FRF and FA, aids in the automation and optimization of the design process, resulting in better product quality, shorter development times, and increased industrial sector efficiency. Algorithm 1 shows the pseudocode of the Firefly algorithm fine-tuned random forest (FA-FRF).

**Algorithm 1: FA-FRF**

```
import random
from sklearn.ensemble import RandomForestClassifier
def initialize_fireflies(num_fireflies, num_features):
fireflies = []
for i in range(num_fireflies):
firefly = {
"position": [random.uniform(0, 1) for _ in range(num_features)],
"brightness": 0  # Placeholder for fitness/brightness
}
fireflies.append(firefly)
```

$$return\ fireflies$$

$$def\ evaluate\_firefly(firefly, dataset):$$

$$features\ =\ firefly["position"]$$

$$rf\ =\ RandomForestClassifier()$$

$$rf.fit(dataset.features, dataset.labels)$$

$$accuracy\ =\ rf.score(dataset.features, dataset.labels)$$

$$firefly["brightness"]\ =\ accuracy$$

$$return\ accuracy$$

$$def\ move\_firefly(firefly, alpha, beta, gamma, num\_fireflies):$$

$$for\ other\_firefly\ in\ num\_fireflies:$$

$$if\ other\_firefly["brightness"]\ >\ firefly["brightness"]:$$

$$distance\ =\ calculate\_distance(firefly["position"], other\_firefly["position"])$$

$$attractiveness\ =\ beta\ *\ math.exp(-gamma\ *\ distance ** 2)$$

$$for\ i\ in\ range(len(firefly["position"])):$$

$$\begin{aligned} firefly["position"][i] +& \\ &= alpha\ *\ (other\_firefly["position"][i]\ -\ firefly["position"][i]) \\ &+\ attractiveness\ *\ random.uniform(-1, 1) \end{aligned}$$

$$def\ calculate\_distance(position1, position2):$$

$$return\ math.sqrt(sum((p1\ -\ p2)\ **\ 2\ for\ p1, p2\ in\ zip(position1, position2)))$$

$$def\ firefly\_algorithm(dataset, num\_iterations, num\_fireflies, num\_features):$$

$$fireflies\ =\ initialize\_fireflies(num\_fireflies, num\_features)$$

$$for\ iteration\ in\ range(num\_iterations):$$

$$for\ firefly\ in\ fireflies:$$

$$evaluate\_firefly(firefly, dataset)$$

$$move\_firefly(firefly, alpha, beta, gamma, num\_fireflies)$$

$$best\_firefly\ =\ max(fireflies, key = lambda\ x: x["brightness"])$$

$$return\ best\_firefly$$

**4. Result**

A laptop running Windows 11 with an Intel i5 7th Gen processor, 16 GB of RAM, and a Python 3.10.1 environment is used to represent our suggested approach. The suggested technique is assessed in terms of Root

Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE) and Symmetric Mean Absolute Percentage Error (SMAPE) compared with the existing approaches, which are Support Vector Regression (SVR), Depthwise Separable Convolutional neural network (DSCNN), and Bidirectional Long Short-Term Memory (BiLSTM)[26].

RMSE is essential for making certain products fulfill quality standards and consumer expectations since they assess design integrity and point up areas for development. A RMSE assessment is indicated in Figure 2. While the traditional methods SVR, DSCNN, and BiLSTM achieved (0.0850), (0.0511), and (0.0594) respectively, our proposed FA-FRF methodology achieved (0.0490). The results show that our proposed technique decreases than the traditional techniques substantially.

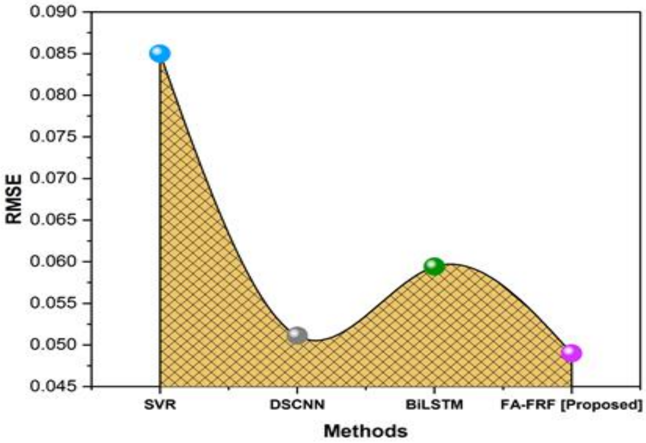


*Figure 2: Output of RMSE*

MAE quantifies absolute variations to determine quality which helps in the evaluation and enhancement of design models and procedures.An MAE evaluation is depicted in Figure 3. While the traditional methods SVR, DSCNN, and BiLSTM achieved (0.0571), (0.0422), and (0.0524) respectively, our proposed FA-FRF methodology achieved (0.0320). The results show that our proposed strategy significantly decreases the current approaches.

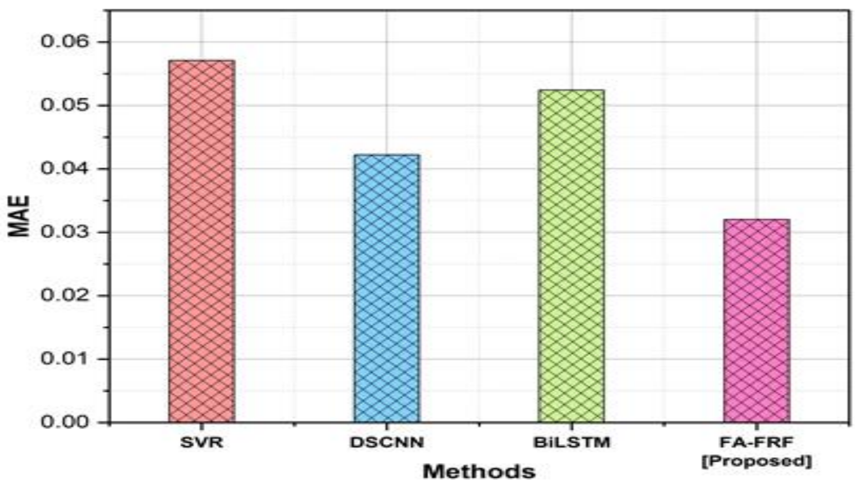


*Figure 3: Output of MAE*

MSE supports the assessment and optimization of designs by attracting attention to areas that require improvement for improved user happiness and product performance. An MSE contrast is illustrated in Figure 4. Although the current techniques SVR, DSCNN, and BiLSTM achieved (0.0072), (0.0026), and

(0.0035) respectively, our proposed FA-FRF methodology achieved (0.0020). The results show that our recommended strategy significantly reduces the use of the current techniques.

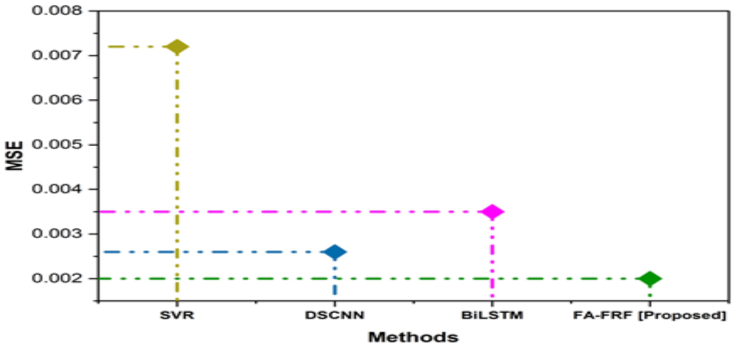


***Figure 4: Output of MSE***

MAPE helps to improve design procedures and decision-making by quantifying the average intensity of failures as proportions. A MAPE evaluation is shown in Figure 5. While the traditional methods SVR, DSCNN, and BiLSTM achieved (6.3006), (4.5046), and (5.2893) respectively, our proposed FA-FRF methodology achieved (3.4137). The results show the existing approaches are minimized by our proposed strategy.

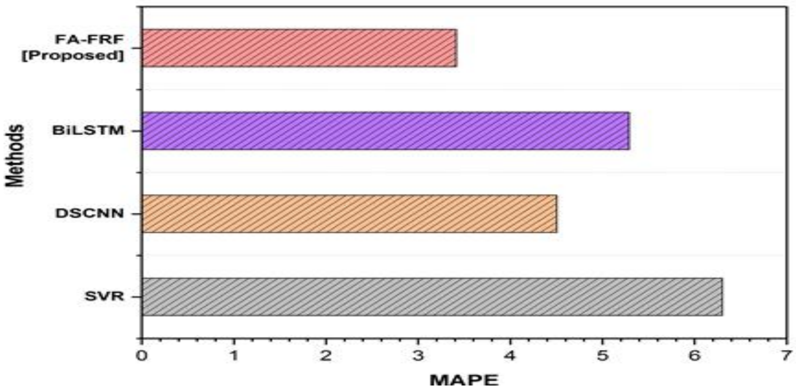


***Figure 5: Output of MAPE***

SMAPE gauges the typical percentage variance among actual and expected values, offering information about design choices worked. An SMAPE comparison is shown in Figure 6. While the traditional methods SVR, DSCNN, and BiLSTM achieved (6.2532), (4.6418), and (5.6673) respectively, our proposed FA-FRF methodology achieved (3.9871). According to the results, our recommended strategy significantly reduces the utilization of the current techniques. Table 2 shows the overall result comparison.

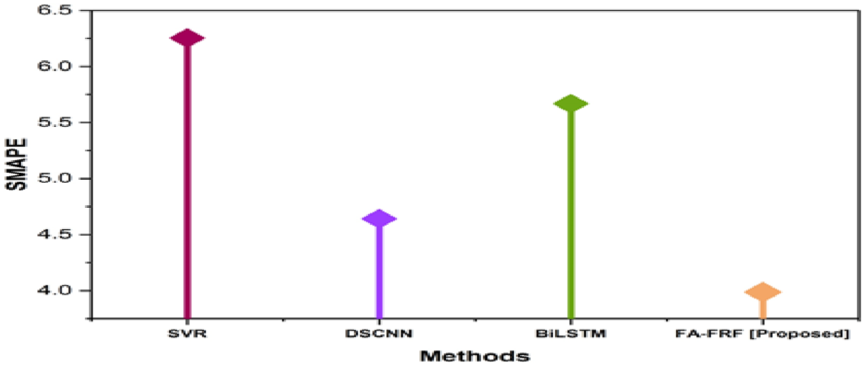


***Figure 6: Output of SMAPE***

**Table 2: Overall result comparison**

| Methods | RMSE | MSE | MAE | SMAPE | MAPE |
|---|---|---|---|---|---|
| SVR | 0.0850 | 0.0072 | 0.0571 | 6.2532 | 6.3006 |
| BiLSTM | 0.0594 | 0.0035 | 0.0524 | 5.6673 | 5.2893 |
| DSCNN | 0.0511 | 0.0026 | 0.0422 | 4.6418 | 4.5046 |
| FA-FRF[Proposed] | 0.0490 | 0.0020 | 0.0320 | 3.9871 | 3.4137 |

**5. Conclusion**

The difficult process of creating industrial products requires the optimization of multiple elements to achieve the necessary levels of performance and quality. The FA-FRF model is introduced in this paper, demonstrating how well it may be used to optimize industrial product design operations. Considering the use of a large dataset that includes important design parameters such as capacity, material composition, production processes, and market segmentation, the study uses methods such as min-max normalization for data pre-processing and ICAfor feature extraction. Through Python implementation, the study attains impressive performance metrics such as RMSE (0.0490), MAE (0.0320), MSE (0.0020), MAPE (3.4137), and SMAPE (3.9871). In industrial environments, the FA-FRF model gives technicians and designers the power to improve decision-making and optimize design outputs, which raises the general integrity and effectiveness of product designs. Its efficiency may differ and it is based on the intricacy of the particular design problem and the potential of the input data, which restricts its applicability to all industrial design situations.The potential for industrial product design in the future encompasses increasing algorithmic efficiency, integrating with AI-driven design platforms, customizing for industry-specific requirements and improving optimization and decision-making in the process of developing new products.

**References**

1. Ullah, I. and Mahmoud, Q.H., 2021. Design and development of a deep learning-based model for anomaly detection in IoT networks. IEEE Access, 9, pp.103906-103926.
2. Liu, X., Liu, Y., Chen, Y. and Hanzo, L., 2019. Trajectory design and power control for multi-UAV assisted wireless networks: A machine learning approach. IEEE Transactions on Vehicular Technology, 68(8), pp.7957-7969.
3. Moosavi, S.M., Jablonka, K.M. and Smit, B., 2020. The role of machine learning in the understanding and design of materials. Journal of the American Chemical Society, 142(48), pp.20273-20287.
4. Zolanvari, M., Teixeira, M.A., Gupta, L., Khan, K.M. and Jain, R., 2019. Machine learning-based network vulnerability analysis of industrial Internet of Things. IEEE internet of things journal, 6(4), pp.6822-6834.
5. Ma, W., Liu, Z., Kudyshev, Z.A., Boltasseva, A., Cai, W. and Liu, Y., 2021. Deep learning for the design of photonic structures. Nature Photonics, 15(2), pp.77-90.
6. Liu, X., Liu, Y. and Chen, Y., 2019. Reinforcement learning in multiple-UAV networks: Deployment and movement design. IEEE Transactions on Vehicular Technology, 68(8), pp.8036-8049.
7. Ma, W., Cheng, F. and Liu, Y., 2018. Deep-learning-enabled on-demand design of chiral metamaterials. ACS nano, 12(6), pp.6326-6334.
8. Muna, A.H., Moustafa, N. and Sitnikova, E., 2018. Identification of malicious activities in industrial internet of things based on deep learning models. Journal of information security and applications, 41, pp.1-11.
9. Li, L., Ota, K. and Dong, M., 2018. Deep learning for smart industry: Efficient manufacture inspection system with fog computing. IEEE Transactions on Industrial Informatics, 14(10), pp.4665-4673.
10. Sanchez-Lengeling, B. and Aspuru-Guzik, A., 2018. Inverse molecular design using machine learning: Generative models for matter engineering. *Science*, *361*(6400), pp.360-365.
11. Jiang, J., Xiong, Y., Zhang, Z. and Rosen, D.W., 2022. Machine learning integrated design for additive manufacturing. Journal of Intelligent Manufacturing, 33(4), pp.1073-1086.

12. Schuh, G., Scholz, P., Leich, T. and May, R., 2020, October. Identifying and analyzing data model requirements and technology potentials of machine learning systems in the manufacturing industry of the future. In 2020 61st International Scientific Conference on Information Technology and Management Science of Riga Technical University (ITMS) (pp. 1-10). IEEE.
13. Tao, F., Cheng, J., Qi, Q., Zhang, M., Zhang, H. and Sui, F., 2018. Digital twin-driven product design, manufacturing and service with big data. The International Journal of Advanced Manufacturing Technology, 94, pp.3563-3576.
14. Fournier-Viger, P., Nawaz, M.S., Song, W. and Gan, W., 2021. Machine learning for intelligent industrial design. In Joint European Conference on Machine Learning and Knowledge Discovery in Databases (pp. 158-172). Springer, Cham.
15. Krahe, C., Bräunche, A., Jacob, A., Stricker, N. and Lanza, G., 2020. Deep learning for automated product design. Procedia CIRP, 91, pp.3-8.
16. Ziegler, M.M., Kwon, J., Liu, H.Y. and Carloni, L.P., 2021, November. Online and offline machine learning for industrial design flow tuning:(Invited-ICCAD special session paper). In 2021 IEEE/ACM International Conference On Computer Aided Design (ICCAD) (pp. 1-9). IEEE.
17. Kun, X., Wang, Z., Zhou, Z. and Qi, W., 2021. Design of industrial internet of things system based on machine learning and artificial intelligence technology. Journal of Intelligent & Fuzzy Systems, 40(2), pp.2601-2611.
18. Li, Y., Lei, G., Bramerdorfer, G., Peng, S., Sun, X. and Zhu, J., 2021. Machine learning for design optimization of electromagnetic devices: Recent developments and future directions. Applied Sciences, 11(4), p.1627.
19. Tufano, A., Accorsi, R. and Manzini, R., 2022. A machine learning approach for predictive warehouse design. The International Journal of Advanced Manufacturing Technology, 119(3), pp.2369-2392.
20. Ghoreishi, M. and Happonen, A., 2020, May. Key enablers for deploying artificial intelligence for circular economy embracing sustainable product design: Three case studies. In AIP conference proceedings (Vol. 2233, No. 1). AIP Publishing.
21. Pessôa, M.P. and Becker, J.J., 2020. Smart design engineering: a literature review of the impact of the 4th industrial revolution on product design and development. Research in engineering design, 31(2), pp.175-195.
22. Paraschos, P.D., Xanthopoulos, A.S., Koulinas, G.K. and Koulouriotis, D.E., 2022. Machine learning integrated design and operation management for resilient circular manufacturing systems. Computers & Industrial Engineering, 167, p.107971.
23. Romeo, L., Loncarski, J., Paolanti, M., Bocchini, G., Mancini, A. and Frontoni, E., 2020. Machine learning-based design support system for the prediction of heterogeneous machine parameters in industry 4.0. Expert Systems with Applications, 140, p.112869.
24. Bodendorf, F. and Franke, J., 2021. A machine learning approach to estimate product costs in the early product design phase: a use case from the automotive industry. Procedia CIRP, 100, pp.643-648.
25. Kuschmitz, S., Ring, T.P., Watschke, H., Langer, S.C. and Vietor, T., 2021. Design and additive manufacturing of porous sound absorbers—A machine-learning approach. Materials, 14(7), p.1747.
26. Zhou, Q., Li, H., Zhang, Y. and Zheng, J., 2023. Product Evaluation Prediction Model Based on Multi-Level Deep Feature Fusion. Future Internet, 15(1), p.31.