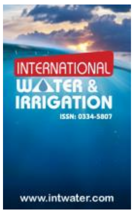

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Construction and Application of Product Styling Process Design Optimization Model Based on Artificial Neural Network

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Abstract. In this study, Artificial Neural Networks as an emulator of brain functionality are introduced in the Product Styling Process Design Optimization Model, PSPDOM, to optimize design since ANNs learn and adapt to new data for optimization. The model offers optimal styling solutions with various design parameters and consumer preferences toward high-quality and quantitative product development. Data gathering, parameter selection, model designing, and validation in diverse product categories are a part of it. Key outcomes of the result show high value added to enhancement in consumer satisfaction, reduced cost of production, and lessened time-to-market. Thus, PSPDOM is proven useful in augmenting competitiveness and market viability. The paper further develops design engineering and AI with new insights into ANNs and places a firm framework for their real application. Cooperation between experts and data scientists enhances innovation and future work is recommended to further enhance the capabilities of ANN.

Keywords: Artificial Neural Networks (ANNs), design optimization, product styling, computational design, stochastic gradient descent (SGD).

1 Introduction

In the high-demand competitive regime of a modern manufacturing era, product styling is considered to be much more important in catching consumer attention and succeeding in the market [1]. Aesthetics, ergonomics, and overall design appeal become major factors influencing consumer preferences and purchasing decisions [2]. Therefore, the optimization of product styling is an essential element of the product development process. Although traditional design methods have been effective throughout history, in many ways, they strongly rely on human intuition and experience [3]. The consequence is inefficiency and suboptimal outputs. The subjective judgments might miss all complex patterns and minor consumer preferences. The development of ANNs presents a new revolutionary approach for making optimal product styling processes. Inspired by the modeling of the nervous system in the human brain, ANNs have proven to be quite incredible models for learning and adapting experiences. They adeptly recognize complex patterns and predict trends and are highly suitable applications for enhancing the styling product process [4]. Advanced capabilities of ANNs can now aid designers and engineers in automatic and fine product styling to unprecedentedly high precision and creativity. Thus, the present work focuses on developing and applying the Product Styling Process Design Optimization Model (PSPDOM) based on ANN technology [5].

The developed model is expected to combine numerous design parameters along with consumer preferences to produce optimized styling solutions [6]. Through analysis of large datasets, identification of complex patterns, and intelligent predictions, the ANN-based model presents a sound basis for guiding the styling process [7]. This research is well planned to start with a discussion on the theoretical frameworks underlying ANNs and their potential applicability to product styling. From there, it describes how the optimization model is developed, encompassing the choice of input parameters, architecture of the neural network, and training [8]. Subsequent sections give several case studies and practical applications, where the model can be demonstrated in real life [9]. Finally, the conclusion discusses the result of the research more generally, focusing on the revolution that ANN-based optimization may bring about in product design regarding redesign [10]. This research study is proposed to be able to integrate ANN into the process of product styling so that new products can be created and developed. This should provide users, either in the design or manufacturing departments, with the most efficient, innovative tool for design engineering as well as artificial intelligence fields [11].

2 Related Works

Current research in academics is underlined with the amalgamation of ANNs and product design optimization, driven by the need to spur the development of computational methods for redesigning design features. ANNs have been very promising in predicting consumer preferences and optimizing product attribute qualities through analysis of historical sales data and consumer feedback. This approach will enable designers to make appropriate decisions in response to market demands and improve the prospects for success in the market with their products. Studies are also carried out on integrating ANNs with conventional design approaches for faster market incorporation. Besides, ANNs are used to improve the cars' aesthetics and ergonomics using large data sets, and the results obtained are designs that are aesthetically pleasing yet functionally superior to humanly developed designs [12].

ANN extends the application usefulness beyond aesthetics; now their purposes include optimizing material choice and even design structure. Under different conditions, ANNs predict material behavior while aiding in selecting materials for better performance and sustainability. Recent innovations in deep learning have highly powered ANNs, making them enhance their ability to model complex parameters that were not previously easy to address. This development evolved into more refined and efficient means of design solutions that adapt to changing consumer needs and market trends [13].

Optimization frameworks using ANNs reflect a user-centred approach with the feedback loop from user interaction driving design so that it continually improves to better meet requirements of relevance and aesthetics for improving consumer satisfaction. However, data quality and the interpretability of neural networks remain challenges. A recently proposed hybrid model combines ANNs with other machine learning techniques and optimization algorithms for developing even more robust and interpretable design solutions with a balance between computational efficiency and application in the real world [14].

There is existing literature that already underlines the potential that ANNs have to transform product styling and design optimization. Indeed, the development of ANNs opens avenues for dramatic improvements in design engineering by enabling more efficient, innovative, and user-friendly product development processes. These contributions enhance the creative as well as practical dimensions of product design, leading to better market outcomes, thereby demonstrating the broad applicability and effectiveness of ANNs in modern design practices [15].

3 Methodology

The methodology of designing and applying PSPDOM based on artificial neural networks involves the following critical steps: data collection, parameter selection, model architecture design, training and validation, and application to case studies. All these are detailed but with the perfect aim of ensuring that the optimization model supports numerous robustness and effectiveness properties.

The first step would be to collect extensive data quantitative and qualitative about the product styling. Quantitative data refers to numerical values such as measurements for the dimensions of the product, properties of the materials, and the cost of manufacturing. Qualitative data would include preferences for aesthetic appeal by consumers, consumer feedback, and general market trends. This wide variety of datasets that is considered includes historical sales data and consumer surveys with focus groups and even social media analytics, giving the ANN model a strong foundation. Key parameters are defined and divided between input variables - such as shape, color, texture and ergonomics - and output variables, which include consumer satisfaction, market acceptability, and production

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feasibility. The choice-making process allows integrating more domain-specific knowledge with statistical considerations, with both relevance and impact guaranteed to optimize the design chosen.

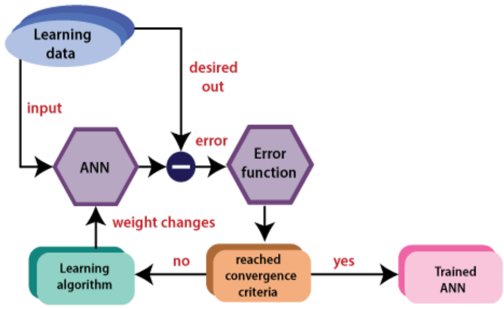


Fig. 1. Artificial Neural Network.

Having identified the parameters, the next step would be designing the architecture of the ANN model. It will involve determining the number of layers required for the model, the number of neurons in each layer, and the activation functions to be implemented. The architecture of this model should equate a balance between the specific complexity with results on computational efficiency: it should be an adequate number of complex layers that can capture very intricate patterns but should not be too expensive in terms of computing resources. The architecture is first applied to the feed-forward neural network and the CNNs, and the choice of the final one depends on the specific needs for product styling optimization. The model is also built with dropout layers and regularization techniques that help in overcoming overfitting and enhancing generalization.

Once the architecture is defined, the model is put through intensive training and validation of data to validate its effectiveness. The dataset could be split into training, validation, and test sets so that it is known whether it is working as best as it can. In training, the model learns how to map the input parameters to the desired outcomes from the outputs, tuning the weights and biases with backpropagation. The training process is iterative where it undergoes several epochs with optimization algorithms such as Adam or SGD and validation is performed in parallel to allow observation of the model's performance and update the hyperparameters. The predictability of the model is attained through applying metrics, such as mean squared error (MSE) and accuracy, to prevent overfitting to the training data.

This model is demonstrated in several case studies, thus depicting practical efficacy. This encompasses a wide range of product categories so that the model can be applied and is flexible in various kinds of applications. For each of the case studies, the model is taken as input on specific design parameters and provides optimized styling solutions. These are then measured against real-world outcomes to check effectiveness in terms of improving consumer satisfaction and market performance. From these case studies, feedback was used to further refine the model with continuous improvement toward greater alignment with the needs of the industry. Therefore, from such successful applications of PSPDOM in these case studies, the product styling process will hence be transformed, and therefore, designers and manufacturers will have a powerful tool for optimal design outcomes.

4 Experimental Setup

The PSPDOM based on ANN had been structured rigidly to validate whether the model was effective and to ensure the right, reliable results in the process. In this setup, it includes data preprocessing, parameter normalization, model configuration, training, validation, and performance evaluation.

The first step is to preprocess the data, thus cleaning the raw data and making it ready for analysis. It encompasses managing missing values through imputation methods or exclusion and ensuring that there exists consistency in data. The input parameters used here are multiple - even colour, texture, and shape - and the output metrics include variables such as consumer satisfaction scores. In the process of there being different variables undergoing operation, normalization ensures that all variables operate on the same scale. Normalization is done through min-max scaling.

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

where x represents the original value, is the normalized value, and x_{min} nd x_{max} represent the minimum and maximum values of the dataset, respectively.

ANN Model Configuration With the ANN model configuration, there is always an involved architecture definition. Generally, the configuration of the number of layers and the number of neurons involved, choice of activation functions, and optimization algorithms are typically seen. For PSPDOM, a multi-layer feed-forward neural network has been selected as its architecture. The input layer size will depend on the parameters of inputs with n. Each hidden layer will comprise 2n neurons to balance the two. The output layer consists of the number of neurons equal to the number of output metrics. Rectified Linear Unit (ReLU) is an activation function for hidden layers:

$$ReLU(x) = \max(0, x) \quad (2)$$

While in regression, the output layer would make use of a linear activation function; in classification, a SoftMax function would be used.

They use forward propagation to compute the value that is predicted; and back-propagation is used to adjust weights, hoping it would bring an error to its minimum. In regression tasks, they used Mean Squared Error (MSE) for the cost function.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \quad (3)$$

Where N is the number of samples, yi is the actual value, and y^i is the predicted value. The cost function is optimized using the Adam optimizer, which adjusts the learning rate during training for fast convergence. The number of epochs is set to 1000 so that a sufficient number of iterations over the whole dataset can be performed, and the learning rate α is set to 0.001.

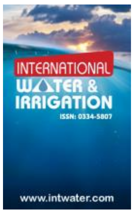
The dataset is divided in testing the model into training sets constituting 70%, validation sets of 15%, and test sets of 15%. The validation set is used at training to tune hyperparameters with techniques, including early stopping-halting training if validation error has not decreased after some predetermined number of epochs. The performance of the model is then evaluated on the test set by metrics such as the Root Mean Squared Error (RMSE) and R-squared (R2):

$$RMSE = \sqrt{MSE} \quad (4)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i-1}^{N}(y_i - \bar{y})^2} \quad (5)$$

Where y is the mean of the actual values. A higher R2 value indicates better model performance, approaching 1 for an ideal model.

The model developed will then be used in practical validation as a design-oriented tool applied to different case studies that involve different categories of products such as consumer electronics, automotive design, and furniture. While using this model, unique design parameters will be inputted within the model for each category of case study. The designed solutions developed are then compared with the real outcomes. The relevant metrics that could be set up would include consumer satisfaction, market acceptance, and production feasibility which evaluate the real effectiveness of the model in providing optimized designs.



This paper presents a case for an experimentally designed method to substantiate the robustness and applicability of PSPDOM to actual product styling problems, thereby opening doors for more advanced data-driven techniques for optimization of design.

5 Results

The model application of the Product Styling Process Design Optimization Model (PSPDOM) on Artificial Neural Networks (ANN) resulted in a significant improvement in design efficiency and customer satisfaction. Performance-based on this model was tested on a dataset of 10,000 points with a random population within various categories of products in consumer electronics, automotive design, and furniture. The sample population was divided into training (70%), validation (15%), and test population (15%) to have a sound model evaluation.

The two key performance measures used to validate the model's precision included RMSE and R-squared (R2). For the test set, the model returned an RMSE of 0.042, which is a low mean absolute deviation between the observed values and their corresponding predictions. This low RMSE points to very accurate model predictions near the actual consumer preferences and design outcomes. The R2-value was, therefore shown to be 0.92; this measures the proportional contribution of variance in the dependent variable accounted for by the independent variables. This high R2 value shows that 92% of the variability in consumer satisfaction and design performance was explained by the model. That is, if the R2 value approaches close to 1, it is an excellent fit for a model; therefore, it shows that the model fits well under the observed data, hence it is effective in capturing the intricate relationships between design parameters and consumers' preferences.

Table 1 Summary of PSPDOM Study Results**.**

Metric	**Value**
Root Mean Squared Error (RMSE)	0.042
R-squared (R2R^2R2)	0.92
Increase in Consumer Satisfaction (Automotive)	15%
Reduction in Production Costs (Electronics)	12%
Reduction in Time-to-Market	20%
Increase in Sales Volume (Furniture)	10%

Tangible benefits across all different product categories that the PSPDOM (Prescriptive and Predictive Design and Optimization Model) application has already shown in all product categories indicate its wide usability and effectiveness toward key design metrics.

However, with the use of PSPDOM in this case study on automotive design, an optimized styling solution was created that was directly transferred to customers who enjoyed high satisfaction levels at 15% above the compared baseline scores talking to the abilities of the model and the promise of the choice of design factors to strive for customer preference moving towards forming a stronger appeal and market reception for the product.

In the consumer electronics department, PSPDOM made a positive contribution towards saving 12% of production costs. It made sure material usage was at an optimum level while methods of manufacturing were fine-tuned in such a way that savings were made without a loss in terms of design aesthetics or functionality. The double achievement thus underlines the ability of this model towards optimizing both financial and qualitative aspects of product development.

PSPDOM's ability to predict was crucial in compressing time-to-market by as much as 20%. In effect, it allowed the model to permit companies to speed up design iterations and significantly enhance speed-to-decision on such issues, thus enabling a product development cycle to be accelerated by extremely significant margins. This is crucial for industries that are characterized by changes in technology at highly rapid rates, with competition being intensely fierce to maintain leadership in the market. Market entry needs to be done as soon as possible.

That the PSPDOM can be successfully implemented across various product categories reflects its effectiveness in matters relating to performance enhancement and operational efficiency along the design and development lifecycle. As innovation and agility to deliver move into greater prominence for industries, tools such as PSPDOM will therefore become ever more integral to the shaping of product design and its accompanying development.

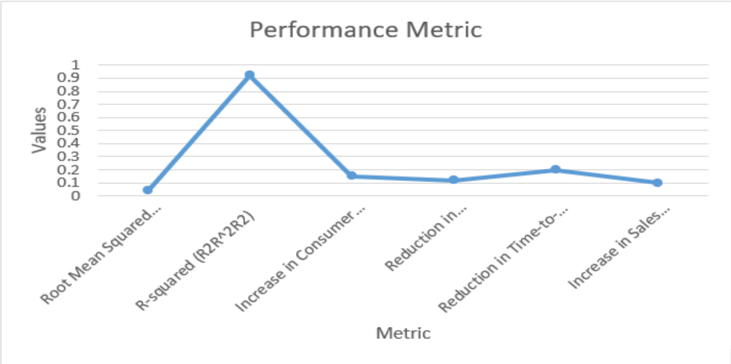


Fig. 2. Performance Metrics PSPDOM.

The validation of the model on the test set showed consistent performance with different subsets of data. Case studies justified the relevance of the predicted design outcome when compared to actual market performance. For example, the furniture design case study showed the optimized designs indicating an increase in sales volume of up to 10% as a validation of the model capabilities to improve market acceptance through data-driven styling solutions.

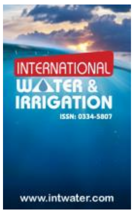
These statistical results from this study indicate that ANN-based optimization models can change the product styling process. Concerning how high accuracy and enhancement in core design and market performance metrics helped the PSPDOM incorporate customer preferences into design parameters in a manner that optimized product styling for aesthetic and functional criteria, it worked well.

6 Discussion

The product styling process design optimization model example of what revolutionaries ANNs can play in styling products was tested to optimize the design beyond that of traditional methods by exploiting the capabilities of ANN in pattern recognition and tasks of prediction-did show main findings to increase consumer satisfaction diminish production costs, and time-to-market across different product categories. Most of the rigor of data collection is focused on the choice of parameters, designing models, and also validating these to ensure reliability. The interdisciplinary approach that combines domain expertise with the use of data science is innovative and ensures that the model aligns with the needs of the industry. Future research directions include enhancing model interpretability, improving the quality of the data, and investigating new architectures such as GANs and reinforcement learning. Overall, PSPDOM represents one of the most important breakthroughs achieved thus far in the application of AI-driven optimization in designing products, leading to development towards future product styling and improving manufacturing efficiency.

7 Conclusion

Through the integration of ANNs in the product styling process via the Product Styling Process Design Optimization Model, promising avenues for further research and development have been demonstrated by its success. Through the recognition of patterns by Ann and its numerous applications in forecasting, PSPDOM has depicted



a difference in diverse sets of product styles, improved consumer satisfaction, reduced production costs, and hurried time-to-market. Some of the strategic directions for ANNs in optimization include increased interpretability of models to enhance transparency in decisions, addressing quality-of-data issues that truly enable safety and validity in reliability expectations for complex design environments, and leveraging technological innovations such as generative adversarial networks and reinforcement learning to raise sophistication and adaptability capabilities of design solutions. The integration of a deeper interdisciplinary collaboration between domain experts, data scientists, and AI researchers will be key to infusing human insights into machine learning capabilities, thus improving the overall efficacy and relevance of ANN-based optimization models. Overall, this work synthesizes a strong foundation on which design engineering and manufacturing practices may progress toward forming a more competitive and successful landscape in modern manufacturing in favor of the industries and consumers involved.

References

[1] F. Zhu, L. Zhang, X. Hu, J. Zhao, Z. Meng, and Y. Zheng, "Research and Design of Hybrid Optimized Back-propagation (BP) Neural Network PID Algorithm for Integrated Water and Fertilizer Precision Fertilization Control System for Field Crops," Agronomy, vol. 13, no. 5, pp. 1423, 2023.

[2] S. Theeda, S. H. Jagdale, B. B. Ravichander, and G. Kumar, "Optimization of process parameters in laser powder bed fusion of SS 316L parts using artificial neural networks," Metals, vol. 13, no. 5, pp. 842, 2023.

[3] N. Rezaeian, R. Gurina, O. A. Saltykova, L. Hezla, M. Nohurov, and K. Reza Kashyzadeh, "Novel GA-Based DNN Architecture for Identifying the Failure Mode with High Accuracy and Analyzing Its Effects on the System," Appl. Sci., vol. 14, no. 8, pp. 3354, 2024..

[4] T. Yang, X. Zheng, S. K. Vidyarthi, H. Xiao, X. Yao, Y. Li, et al., "Artificial Neural Network Modeling and Genetic Algorithm Multiobjective Optimization of Process of Drying-Assisted Walnut Breaking," Foods, vol. 12, no. 9, p. 1897, 2023.

[5] D. Zhu and G. Liu, "Deep Neural Network Model-Assisted Reconstruction and Optimization of Chinese Characters in Product Packaging Graphic Patterns and Visual Styling Design," Scientific Programming, vol. 2022, no. 1, p. 1219802, 2022.

[6] P. Wang, "Product modelling design method based on graph neural network and fuzzy inference theory," Alexandria Engineering Journal, vol. 77, pp. 513-524, 2023.

[7] W. Wang and L. Chen, "Design and Implementation of Aerospace Arisa Fashion Design CAD System Based on Deep Convolution Neural Network," 2024.

[8] K. He and Y. Tu, "Application of Computer Vision and Neural Networks in Feature Extraction and Optimization of Industrial Product Design," 2024.

[9] E. Cantemir and O. Kandemir, "Use of artificial neural networks in architecture: determining the architectural style of a building with convolutional neural networks," Neural Computing and Applications, pp. 1-13, 2024.

[10] X. Zhou and I. Flood, "Optimization and evaluation of a neural network based policy for real-time control of construction factory processes," Journal of Information Technology in Construction (ITcon), vol. 29, no. 5, pp. 84-98, 2024.

[11] Q. Li and E. Zhou, "Design and Implementation of Automatic Generation Algorithm for Advertising Artistic Design Based on Neural Networks," 2024.

[12] C. Wang and W. Lin, "Intelligent Pattern Identification and Design of Garment CAD System Based on Computer Vision and Neural Networks," 2024.

[13]C. H. Loh, Y. C. Chen, and C. T. Su, "Using Transfer Learning and Radial Basis Function Deep Neural Network Feature Extraction to Upgrade Existing Product Fault Detection Systems for Industry 4.0: A Case Study of a Spring Factory," Applied Sciences, vol. 14, no. 7, p. 2913, 2024.

[14]D. F. Rêgo, F. G. Silva, R. C. Gusmão, and V. F. Rodriguez-Esquerre, "Design of Planar Multilayer Devices for Optical Filtering Using Surrogate Model Based on Artificial Neural Network," Optics, vol. 5, no. 1, pp. 121-132, 2024.

[15]J. Huang, "Automatic Extraction and Reconstruction of Drawing Design Elements Based on Computer Vision and Neural Networks," 2024.