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On the Applications of Neural Networks in Industrial Design: A Survey of the State of the Art

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Abstract: This study provides an overview of the opportunities for applications of artificial neural networks in industrial design. It offers the knowledge of the architecture of different types of neural network models, main training tools and the current trends in neural networks applications to problems in industrial design area. The study also discusses the role that neural network models can play in complex engineering design problems. Since, neural networks are relevant in various contexts including many optimization and control problems, the study can be useful in industrial design and engineering design tasks of diverse interest.

Key words: Neural networks, industrial design, optimization, control, prediction, automation, pattern recognition

INTRODUCTION

Artificial Neural Networks (ANNs) or commonly known as Neural Networks (NNs) are effective, efficient and successful in providing a high level of capability in handling complex and noncomplex problems in many spheres of life. As such ANNs are capable of handling problems in agriculture, science, medical science, education, finance, management, security, engineering, trading commodity and art (Abiodun *et al*., 2018). Recently, applications of ANNs have been increasing in any aspect of life. More and more development tools have been proposed in the literature.

The strong interest in the product development and creation of best customer experience has lead to extended research activities on the applications of NNs in industrial design. In the design stage how to generate creative design ideas with desired image feelings is a very important problem that the designer pays much attention to Hsiao and Huang (2002).

The industrial design process very often includes tasks related to optimization problems, pattern recognition, control and forecasting. In addition, the methods of collecting design information are very important factors in modern product development process. NNs are recognized as ones of the best techniques for such tasks (Hsiao and Huang, 2002) due to their:

- Learning ability
- Storage ability
- Fault tolerance
- Inductive ability
- Parallel handling ability

Recently, there are excellent overview articles about the applications of NNs in transportation, computer security, banking, insurance, properties management, robotics, business. See, for example, Abiodun *et al*. (2018), Amalraj (2017), Horne *et al*. (1990) and Li (1994) and the references therein.

A very good overview on the applications of neural network concepts and techniques to design and manufacturing is the book edited by Wang and Takefuji (1993). The book reviews the state-of-the-art of the research activities, highlights the recent advances in research and development and discusses the potential directions and future trends along this stream of research. However, to the best of researcher's knowledge there is not a survey or a single book addressing the potential roles of ANNs for design and manufacturing, since, 1993. In this study, a review of the recent results on neural networks applications in industrial design is proposed.

Main text

Neural networks: An ANN is made up of many artificial neurons which are correlated together in accordance with explicit network architecture. The objective of the neural network is to convert the inputs into significant outputs (Amalraj, 2017). Such systems have been derived through models of neurophysiology (Horne *et al*., 1990). As in the human brain, these networks are capable of learning from examples. An ANN can be comparable machine produced to function the same way the human brain performs a given task of interest (Haykin, 2009). Most networks are based on supervised learning algorithms in which pairs of input and desired output are shown to them during a training session (Malasri *et al*., 2006).

The transformation of the inputs to desire outputs depends on the connections between the units (neurons) in a NN, the number of layers in its architecture and the signals that each unit receives and send. The connection weights are similar to synaptic biological impulses and determine the functionality and behavior of the NN (Nelson and Illingworth, 1994).

There are two main issues in building a network Simpson *et al*. (1997) specifying the architecture and training the network to perform well with reference to a training set. If the architecture is made large enough, a neural network can be a nearly universal approximator (Rumelhart *et al*., 1994).

Training a neural net refers to determining the proper values of all the weights in the architecture and is accomplished most commonly through backpropagation (Rumelhart *et al*., 1994). The type of a NN Model depends on:

- Architecture: there are NNs with different number of layers and connections between the units
- Connection weights: the strengths or amplitudes of the connections between the units
- Input and output signals
- Activation functions for limiting the amplitude of the output of a neuron
- Training rules

Architecture: The architecture of an ANN is determined by the tasks (Fig. 1). In general, we may identify three fundamentally different classes of network architectures (Haykin, 2009):

Single-layer feedforward networks: Constructed of an input layer of source nodes that projects directly onto an output layer of neurons (computation nodes) but not vice versa.

Multilayer feedforward networks: One or more hidden layers whose computation nodes are correspondingly called hidden neurons or hidden units are situated between the input and output layers.

The function of hidden neurons is to intervene between the external input and the network output in some useful manner. By adding one or more hidden layers, the network is enabled to extract higher-order statistics from its input. An architecture of a typical NN with one hidden layer is showed in Fig. 2.

Recurrent networks: They have at least one feedbackloop. For example, a recurrent network may consist of a single layer of neurons with each neuron feeding its output signal back to the inputs of all the other neurons. Recurrent NNs, also may be constructed just by an input and an output layers or they may have hidden layers.

In any of the three different types of NNs, neural network layers are independent of one another that is a specific layer can have an arbitrary number of nodes. The nodes (neurons, units) are structural element in each layer. A typical graph of a neuron is given in Fig. 3.

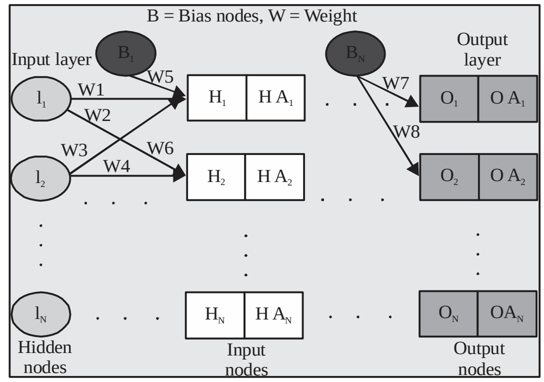

Fig. 1: A typical NN architecture (Abiodun *et al*., 2018)

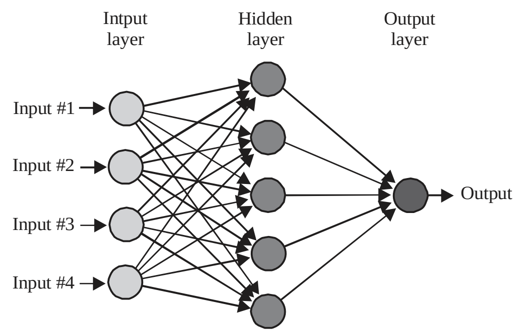

Fig. 2: A scheme of a NN with one hidden layer (Amalraj, 2017)

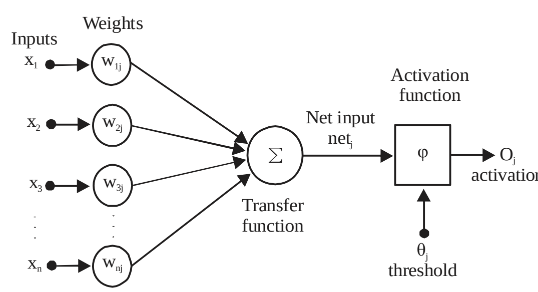

Fig. 3: A model of a neuron (Haykin, 2009)

The most complicated step in building a NN is the choice of an activation (transfer) function for each neuron that defines the output of the neuron. The most commonly used activation functions in the construction of neural networks are the following:

- Threshold (Heaviside) function $f(x) = \begin{cases} 0, & x < 0, \\ 1, & x \geq 0 \end{cases}$ that assumes just value of 0 and 1
- Sigmoid function $f(x) = 1/1+e^{-x}$ that assumes a continuous range of values from 0 to 1

- Hyperbolic function $f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$ that assumes a continuous range of values from -1 to 1
- Sigmoid function f(x) = 1/2(|x+1|+|x-1|)

Training tools: Since, the field of ANNs has been the center of intense research activities in science and engineering for over than four decades as a result, a large set of software tools used to train NNs have been developed. Thus, making a selection of the adequate tool is a difficult task for new researchers and practitioners in industries who are applying neural networks to industrial design. A large survey of the solutions available as well as lists and explains their characteristics and terms of use which is very useful for the ANN users to choose the most appropriate tool for the design application is provided by Baptista and Morgado-Dias (2013). Following the information in it, the most popular training techniques are:

- Back propagation
- Batch training
- Batch version of the backpropagation
- Batch training with weight and bias learning rules
- Bayesian regularization
- Conjugate gradient
- Conjugate gradient descent
- Competitive learning
- Cyclical order incremental update
- Delta-bar-delta
- Enhanced self-aware algorithm
- Evolutionary gradient
- Fast fixed-point algorithm
- Fixed global adaptive
- Fletcher-powell conjugate gradient back propagation
- Genetic algorithm
- Gradient descent back propagation
- Gradient descent with adaptive learning rule back propagation
- Gradient descent with momentum and adaptive learning rule backpropagation
- Gradient descent with momentum back propagation
- Recursive prediction error (Gauss-Newton)
- Incremental training
- Iterated generalized least squares
- k-means
- Lazy Bayesian rules
- Learning vector quantization
- Leabra; A29 Levenberg-Marquardt
- Memory-saving implementation of the LM
- Neuron by neuron algorithm
- Polak-Ribie're conjugate gradient back propagation
- Powell-Beale conjugate gradient back propagation
- Quasi-Newton
- Quasi-Newton (limited memory)
- Quick propagation
- Recursive (incremental) version of backpropagation
- Resilient Propagation (RPROP)
- Self-aware algorithm
- Scaled conjugate gradient backpropagation
- Soft competitive learning
- Step by step
- Stability issues
- Sequential minimal optimization algorithm
- Weight perturbation
- Weight update driven node splitting
- Weight update issues

The most common set of requirements for any tool is the operating system (Baptista and Morgado-Dias, 2013).

Applications in industrial design: In this section, the most useful applications of ANNs in industrial design tasks are reviewed.

Optimization: One of the main applications of NNs in industrial design tasks is in solving of optimization problems. In numerous studies a simulated neural network is used for such problems. In the study, Liu *et al*. (2008) after generating many samples by experiments, the expected values of samples and the simulated values of neural network which is constructed by the genetic algorithm are used for grey relational analysis and the design variables which have a little effect for design result are deleted from series analysis, so as to obtain the effect rules of the design variable to the outputs directly. The design variables to design result are analyzed many times to seek the right design variable information for resolving concrete engineering design problem. Based on the grey relational analysis between the gas hold-up and structure parameters of mechanically agitated reactors, the results show that this effective method which provides a good design idea for solving the design problem.

It is also well know that the engineering design problems as rule contain finding the global optimum in the space with many local optima. Certain class of optimal design problems contains multiple global extremes. Desirably all or as many as possible global extremes should be found (Majak *et al*., 2008).

There are three characteristics in engineering design optimization problems: the design variables are often discrete physical quantities the constraint functions often cannot be expressed analytically in terms of design variables in many engineering design applications, critical constraints are often "pass-fail", 0-1 type binary constraints (Hsu *et al*., 2003). The main goal in the optimization problems is the evaluation of an optimal solution that will guarantee the quality and will meet customer expectations.

For example by Hsu *et al*. (2003) a sequential approximation method specifically for engineering optimization problems with the three characteristics cited above is presented. In this method a back-propagation neural network is trained to simulate a rough map of the feasible domain formed by the constraints using a few representative training data. A training data point consists of a discrete design point and whether this design point is feasible or infeasible. A search algorithm then searches for the optimal point in the feasible domain simulated by the neural network. This new design point is checked against the true constraints to see whether it is feasible and is then added to the training set. The neural network is trained again with this added information in the hope that the network will better simulate the boundary of the feasible domain of the true optimization problem. Then, a further is made for the optimal point in this new approximated feasible domain. This process continues in an iterative manner until the approximate model locates the same optimal point in consecutive iterations. A restart strategy is also employed, so that, the method may have a better chance to reach a global optimum. Design examples (the minimum cross-sectional area design of a welded I-beam, subject to bending and compression loads and the minimum volume design of a helical compression spring, subject to an axially guided constant compression load) with large discrete design spaces and implicit constraints are solved to demonstrate the practicality of this method.

An optimization approach that integrates ANNs is proposed by Majak *et al*. (2008). A number of engineering design problems including: design of car frontal protection system, modeling of new composite from recycled GFP, design of composite bathtub, material parameters identification problem for advanced yield criteria and optimal material orientation problem of orthotropic linear elastic 3D materials are solved using the global optimization technique.

Automation: The necessity of using of ANNs in industrial design problems lies partly on the fact that they are very appropriate in the automation processes in real design practice.

Automated design is the process by which an object is designed by a computer to meet or maximize some measurable objective. A trained network can be used to evaluate the quality or fitness of the design several orders of magnitude faster (Hennigh, 2017). This is one of the distinct benefits of the neural network approach over other automated design approaches.

Moreover, the engineering design work often requires the use of design aids such as look-up tables and graphical plots. These tables and plots are created from experimental data for which no simple mathematical relationship is available. Reading values from these tables/plots typically involves interpolation of the available data which can be time-consuming and error-prone (Malasri *et al*., 2005). In such cases, data can be read from a graphical design aid and a neural network can be trained as an automated engineering aid (Malasri *et al*., 2005).

Retrieval: This application of ANNs is of great practical value to industry because it aids in the identification, retrieval and reuse of engineering designs, potentially saving large amounts of nonrecurring costs. By Caudell *et al*. (1994) a neural information retrieval system is described which is in production within the Boeing Company and has been developed for the identification and retrieval of engineering designs. Two-dimensional and three-dimensional representations of engineering designs are input to adaptive resonance theory neural networks to produce clusters of similar parts. The trained networks are then used to recall an appropriate cluster when queried with a new part design. Later on, Smith *et al*. (1997) reviewed the application, the neural architectures and algorithms and give the current status and the lessons learned in developing a neural-network system for production use in industry.

Simulations: Simulations are ones of the most effective methods in the design of manufacturing systems. Typical reasons for simulation of a manufacturing system includes evaluating the capacity and equipment utilization, identifying bottlenecks in the system, comparing the performance of alternative designs. Simulation is often coupled with artificial intelligence techniques to provide an efficient decision making framework. In several studies NNs are used for the design of a manufacturing system. Cakar and Cil (2004) used four different priority rules in the designed ANN. As a result four different design alternatives are obtained from the trained ANN. Performance measures of a manufacturing system are given to the ANN which then gives a design alternative. The design alternatives are evaluated in terms of performance measures and then the best design alternative is selected from four different alternatives.

Pattern recognition, prediction and decision making: It is well known that NNs are able to recognize patterns and as a result are successful technologies in prediction and decision making. Numerous articles addressed such important applications of ANNs in industrial design.

A neural network based approach can be used for product design form. A backpropagation neural network (Fig. 4) has been presented by Chen and Chang (2016) to predict the likely consumer response to any arbitrary product form.

A neural network based approach is also applied by Chen *et al*. (2010) to determine the best design

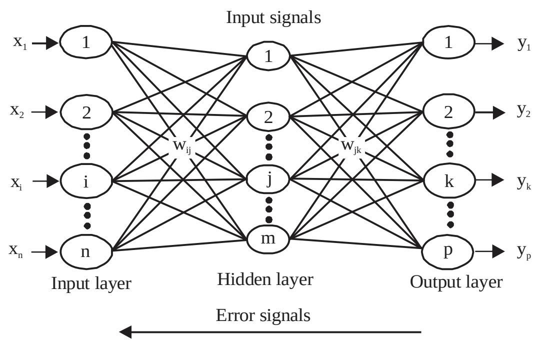

Fig. 4: Three-layered backpropagation neural network structure proposed by Chen and Chang (2016)

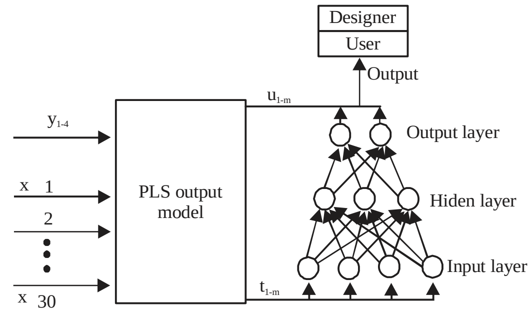

Fig. 5: NN Model structure used for forms and external appearance of sports shoes (Shieh and Yeh, 2013)

combination of product form elements that match a given product value represented by eco-product value attributes. An experimental study has been conducted on office chairs to examine whether the design elements, especially, the armrest type, used on an office chair affects the consumer's perception of the office chair. With the NN Model, an office chair design database is built consisting of 960 different combinations of design elements, together with their associated eco-product value attributes. The application of the design database provides product designers with the best combination of product form elements for examining the aesthetic, functional and environmental-friendly attributes to an office chair design and facilitating the eco-product form design process.

In the study of Hsiao and Huang (2002) experimental results are analyzed by a back-propagation neural network which establishes the relationships between product form parameters and adjective image words. The sigmoid activation function $f(x) = 1/1+e^{-x}$ is applied. A database for the connections among the design elements, product images and shape generation rules has been constructed. The results allow changing the configuration parameter(s) until the product shape is acceptable. In this manner, the designed product can fit more closely to the consumer's desire. Chair design has been taken as a case study but this prediction approach can be used to develop other products. A similar approach has been applied by Hsiao and Tsai (2005) where an electronic door lock design has been chosen as the subject of the current investigation.

The use of a neural network predicting cushion thickness, lowest stress and maximum stress based on the user's provided input of product fragility and drop height has been investigated by Malasri *et al*. (2006). The used NN consists of 2 input cells (product fragility and drop height), 10 hidden cells and 3 output cells (cushion thickness, lowest static and maximum static).

Very recently a physics-driven regularization method for training of deep neural networks for use in engineering design and analysis problems such as aerodynamic design optimization of passenger vehicles has been introduced (Nabian and Meidani, 2020). The method is focused on the prediction of a physical system for which in addition to training data, partial or complete information on a set of governing laws is also available.

Neural networks can also be useful in establishing of predictive models for the design of forms and external appearance of sports shoes (Shieh and Yeh, 2013).

The predictive system developed a specific type of NNs maintains stability or robustness for linear data processing and predictive capability with non-linear data. This allows sports shoe designers to provide the best reference combinations for specific product images when creating conceptual designs of novel shoe appearance. The system can present an appropriate external form of running shoe in the user interface as long as an adjective target value is provided by the designer (Fig. 5).

A systematic approach based on ANNs to reduce the computational burden of battery design by several orders-of-magnitude is presented recently by Wu *et al*. (2018). Two neural networks (Fig. 6) are constructed using the finite element simulation results from a thermo-electrochemical model. The researchers highlight the value of neural network in handling the non-linear, complex and computationally expensive problem of battery design and optimization.

Control and stability: Control and stability of processes are ones of the main futures of a neural network system. Such futures are of a crucial important in many industrial design tasks.

To control the emotional lighting a neural network for emotional colors reasoning is designed by Park and Kim (2018). A mono image scale and an adjective image scale are used to extract the emotional colors in accordance with the emotional languages. The designed neural network is evaluated by the data. The experimental results showed that emotional lighting system through the proposed neural network can be controlled and adjusted in some situations through learning process with interval sets to handle emotional uncertainty.

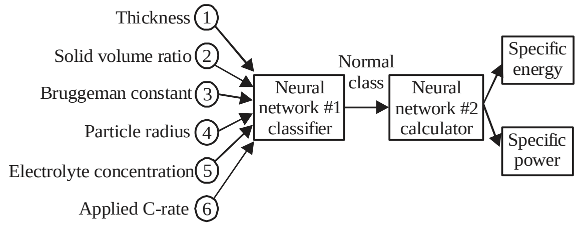

Fig. 6: A neural network scheme for battery design (Wu *et al*., 2018)

Properly designed experiments are essential for effective computer utilization. The traditional approach in engineering is to vary one parameter at a time within a computer analysis code and observe the effects, or to randomly assign different combinations of factor settings to be used as alternative analyses for comparison. Experimental design techniques developed for effective physical experiments, however are being applied for the design of engineering computer experiments to increase the efficiency (computer time) and effectiveness of these analysis codes. After selecting an appropriate experimental design and performing the necessary computer runs, the next step involves choosing an approximating model and fitting method. Many alternative models and methods exist but NNs are found to be one of the most prevalent in the literature (Simpson *et al*., 1997).

By Stamova *et al*. (2013) a NN models has been proposed that is applicable in numerous practical problems including industrial design tasks. Criteria for impulsive control of the NN are offered in this study.

One of the most investigated stability problems in neural network behavior is the problem of exponential stability of the equilibrium (steady) states of the model. If an equilibrium of a neural network is globally exponentially stable, it means that the domain of attraction of the equilibrium point is the whole space and the convergence is in real time. This is significant both theoretically and practically. Such neural networks are known to be well-suited for solving some class of optimization problems. In fact, a globally exponentially stable neural network is guaranteed to compute the global optimal solution independently of the initial condition which in turn implies that the network is devoid of spurious suboptimal responses. Also, the exponential stability guarantees a fast convergence rate.

Since, the fast convergence to an optimal solution is very important in contemporary industrial design tasks related to the use of trained data, therefore, it is necessary to investigate different stability techniques for NNs.

For example, in the study (Stamova and Stamov, 2014a) some abrupt changes effects on the stabilization of a NN Model with wide applications have been investigated. The proposed NN Model has applications in solving optimization problems. It is worth to note that such impulsive control problems have been an object of numerous investigations related to the applications of these models to almost every domain of applied sciences (Stamova and Stamov, 2014b).

Some efficient criteria that guarantee global asymptotic stability have been also proposed for ANNs with supremums (Stamova *et al*., 2014a, b). The developed criteria can be used in the design of globally asymptotically stable NNs applicable in industrial design. Indeed, in the theory of automatic control of various technical systems it is often the case that the law of regulation depends on the supremum values of some regulated state parameters over certain time intervals. Since, the maximum function has very specific properties, it makes the NN strongly non-linear and requires independent study of its qualitative properties. To understand the dynamics, qualitative behavior and control of such NNs, mathematical models are essential (Stamova *et al*., 2014b).

CONCLUSION

In this review study applications of ANNs in industrial design are discussed. The study offers a comprehensive overview of the current state-of-the-art in this direction. It is demonstrated that the NN approach has been applied in numerous industrial design tasks such as optimization, pattern recognition, prediction, decision making, control and stability. In addition, it is shown that ANNs has significant advantages over some other models (statistical models) when both are relatively compared. For example, in ANN Models there are no assumptions about data properties or data distribution. Therefore, ANNs are more useful in practical application. Also, unlike some statistical models that require certain hypothesis for testing, ANN Models do not require any hypothesis. ANNs are very flexible, data reduction models, encompassing nonlinear regression models and discriminant models (Abiodun *et al*., 2018).

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