Neural Networks for Cost Estimation of Shell and Tube Heat Exchangers

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Abstract—**The objective of this paper is to develop and test a model of cost estimating for the shell and tube heat exchangers in the early design phase via the application of artificial neural networks (ANN). An ANN model can help the designers to make decisions at the early phases of the design process. With an ANN model, it is possible to obtain a fairly accurate prediction, even when enough and adequate information is not available in the early stages of the design process. This model proved that neural networks are capable of reducing uncertainties related to the cost estimation of a shell and tube heat exchangers.**

Keywords: Cost Estimation, Heat Exchangers, Neural Networks, Shell and Tube.

1 Introduction

Cost estimation is a key factor during the development phases of manufactured products. Early approximations of cost as a function of a set of general characteristics help designers in decisions such as selecting materials, production processes and mainly morphological characteristics of the product. Studies have shown that the greatest potential for cost reduction is at the early design phases, where as much as 80% of the cost of a product is decided. As the design phase itself accounts for a relatively small percentage of the total development cost, devoting a greater effort to design to cost is a reasonable and necessary step towards optimizing product costs. Making a wrong decision at this stage is extremely costly further down the development process. Product modifications and process alterations are more expensive the later they occur in the development cycle. Thus, cost estimators need to approximate the true cost of producing a product. In addition, since cost estimating is the start of the cost management process and influences the 'go/no-go' decisions concerning a new product development, ideally, these go decisions regarding new product development or product design changes must be based on quantitative analysis instead of guesswork. Rush et all. [2] examine both traditional and more recent developments in cost estimating techniques in order to highlight their advantages and limitations. The analysis includes parametric estimating, feature based costing, artificial intelligence, and cost management techniques. Niazi et all. [4] provide a detailed review of the state of the art in product cost estimation covering various techniques and methodologies developed over the years. The overall work is categorized into qualitative and quantitative techniques. The qualitative techniques are further subdivided into intuitive and analogical techniques, and the quantitative ones into parametric and analytical techniques. Curran et all. [5] provide a comprehensive literature review in engineering cost modeling as applied to aerospace. Three main quantitative approaches can be identified for cost estimation purposes:

Analogy-based techniques: these techniques are based on the definition and analysis of the degree of similarity between the new product and another one, which has been already produced by the firm.

The parametric method: the cost is expressed as an analytical function of a set of variables that consist or represent some features of the product which are supposed to influence mainly the final cost of the product. These functions are called Cost Estimation Relationships (CERs) and are built using statistical methodologies.

Analytical Models: in this case the estimation is based on the detailed analysis of the manufacturing process and of the features of the product. The estimated cost of the product is calculated in a very analytical way, as the sum of its elementary components, constituted by the value of the resources used in each step of the production process (raw materials, components, labor, equipment, etc.). Due to this, the engineering approach can be used only when all the characteristics of the production process and of the product are well defined. Therefore, the application of this approach is limited to situation where a great amount of input data is available.

Through a review in the cost estimation literature it can be observed that an incipient number of cases that use artificial intelligence (AI) techniques have been reported. These techniques constitute the last generation of tools for manufactured product cost estimation. The basic concept behind the application of AI in cost estimating is to

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imitate the behavior of a human expert in determining the main variables that rule (and in what extend they do) the final cost of a manufactured product. Thus far, the most used AI technique in cost estimation is the Case Based Reasoning. This technique is similar, in essence, to the analogy based technique. AI techniques allow model, store and reuse information and to capture the relative knowledge about products yet produced for adapting it to new situations i.e. new products under development. [1] proposed Case-Based Estimator (CBE). CBE is a small model, consisting of five input features, one output and a small case base. According to the authors, an experiment was performed to assess the ability of two retrieval mechanisms (one a simple mathematical formula, the other an adaptation of the ID3 decision tree generating algorithm) to measure similarity. The simple formula was found to be more preferable, both in terms of consistency and development effort. Another case based system for the cost estimation is presented in [6]. They proposed an intelligent system for predicting of total cost of stamping tools. The work is limited to tools for manufacture of sheet metal products by stamping. On the basis of target and source cases, the system prepares the prediction of costs. The results show that the quality of predictions made by the intelligent system is comparable to the quality assured by the experienced expert. Artificial Neural Networks (ANN) has been the most explored AI based technique in research on cost estimation. Neural networks, as non-parametric approximators attempt to fit curves through data without being provided a predetermined function with free parameters. Neural networks are therefore able to detect hidden functional relationships between product attributes and cost, i.e. relationships unknown to the cost engineer [7]. investigates the potential of neural networks to support cost estimation at the early stage of product development. The cost estimation performance is compared to conventional methods, i.e. linear and non-linear parametric regression. Neural networks achieve lower deviations in their cost estimations. Cavalieri et all. [19] reported the compared results of the application of two different approaches-respectively parametric and artificial neural network techniques-for the estimation of the unitary manufacturing costs of a new type of brake disks produced by an Italian manufacturing firm. Kim and Han [8] proposed hybrid artificial intelligence techniques to resolve these two problems. Genetic algorithms are used to identify optimal or near-optimal cost drivers. In addition, artificial neural networks are employed to allocate indirect costs with nonlinear behavior to the products. Empirical results show that the proposed model outperforms the conventional model. Some applications of ANN not properly in cost estimation but in cost drivers estimation in Activity based Costing (ABC) are reported in the literature. Kim and Han [9] applied hybrid models of neural networks and genetic algorithms (GA) to cost estimation of residential buildings to predict preliminary cost estimates. Kwan and Ahn [10] presented a learning algorithm based estimation method for maintenance cost as life cycle cost of product concepts.

Seo et all. [11] explores an approximate method for providing the preliminary life cycle cost. Learning algorithms trained to use the known characteristics of existing products allow the life cycle cost of new products to be approximated quickly during the conceptual design phase without the overhead of defining new LCC models. Artificial neural networks were trained to generalize product attributes and life cycle cost data from preexisting LCC studies. Because of this approach, there is still considerable uncertainty within the estimate, which can affect the final result. One approach that arises is applying fuzzy sets and fuzzy reasoning for modeling situation using linguistic variables. With this approach called fuzzy logic, it is possible to handle the uncertainty in cost estimation problems that cannot be addressed by the traditional techniques. This uncertainty is product of a sort of tolerance for imperfection of human when is transferring ideas or information as the emission of opinions. Shehab and Abdalah [12] proposed an intelligent knowledge-based system for product cost modeling. The developed system has the capability of selecting a material, as well as machining processes and parameters based on a set of design and production parameters; and of estimating the product cost throughout the entire product development cycle including assembly cost. The proposed system is applied without the need for detailed design information, so that it can be used at an early design stage. Fuzzy logic-based knowledge representation is applied to deal with uncertainty in the knowledge of cost model to generate reliable cost estimation. The system has been validated through a case study. Other proposals include the use of non traditional techniques for cost estimation. Koonce et all. [13] presents the design and implementation of a customizable cost integration tool to support design time optimization that considers cost as an objective function or constraint. Giachetti and Arango [14] reported an activity-based printed circuit board (PCB) cost estimation model. The proposed model estimates PCB cost based on the design parameters. The activities are defined so that the design decisions become the cost drivers and thus enable the cost estimation model to be utilized early in design process when sufficient time remains to make design changes. The cost model is used to rapidly compare different PCB design alternatives and lets the designer assess the impact of their decisions on final cost and aid the designer in generating lower cost alternatives. Zbayraka et all. [15] discussed the implementation of the Activity Based Costing (ABC) approach alongside a mathematical and simulation model to estimate the manufacturing and product cost in an automated manufacturing system. ABC was been used to model the manufacturing and product costs. An extensive analysis was been carried out to calculate the product

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costs under the two strategies. The comparison of the two strategies in terms of effects on the manufacturing and product costs are carried out to highlight the difference between the two strategies. H'midaa et all. [16] introduces the new concept of Cost Entity and proposed two models, a Product Model and a Costgrammes Model. The cost estimating reasoning procedure, that takes into account alternative process plans of a product, is modeled and solved by a constraint satisfaction problem (CSP). In [18] a framework for estimating the manufacturing cost in terms of a feature-based approach is proposed. This system tends to estimate the manufacturing cost of a design according to the shapes and precision of its features. The approach integrates a feature-based CAD model and a database-storing product and process cost.

2 Heat Exchangers Design

Shell-and-tube heat exchangers are probably the most common type of heat exchangers applicable for a wide range of operating temperatures and pressures. They have larger ratios of heat transfer surface to volume than double-pipe heat exchangers, and they are easy to manufacture in a large variety of sizes and flow configurations. They can operate at high pressures, and their construction facilitates disassembly for periodic maintenance and cleaning. Shell-and-tube heat exchangers find widespread use in refrigeration, power generation, heating and air conditioning, chemical processes, manufacturing, and medical applications. A shell-and-tube heat exchanger is an extension of the double-pipe configuration. Instead of a single pipe within a larger pipe, a shell-and-tube heat exchanger consists of a bundle of pipes or tubes enclosed within a cylindrical shell. One fluid flows through the tubes, and a second fluid flows within the space between the tubes and the shell (Fig. 1).

The main purpose of a heat exchanger is to capture heat that would otherwise be lost through waste gases or liquids and return that heat to some stage of the production process. Heat exchangers have been used in various industrial processes for more than 60 years. The most commonly used type of heat exchanger is the shell-and-tube heat exchanger, the optimal design of which is the main objective of this study. Various strategies are applied for the optimal design of heat exchangers. The main objective in any heat exchanger design is the estimation of the minimum heat transfer area required for a given heat duty, as it governs the overall cost of the heat exchanger. However there is no concrete function that can be expressed explicitly as a function of design variables and in fact many numbers of discrete combinations of the design variables are possible.

Early cost estimate of a part is important information and forms a basis for preparing quotations, which are competitive from a market point of view. The cost of any highly

A	Removable channel and cover	1.03
B	Integral Cover	1.00
C	Integral with Tubesheet removable cover	1.06
N	Channel Integral with tubesheet and removable cover	1.05
D	Special High Pressure closures	1.60

Table 1: Correction factor for front or stationary head types.

L	Fixed Tube Sheet Like "A" Stationary Head	0.83
M	Fixed Tube Sheet Like "B" Stationary Head	0.80
N	Fixed Tube Sheet Like "C" Stationary Head	0.85
P	Outside Packed Floating Head	1.04
S	Floating Head with Backing Device	1.00
T	Pull-Through Floating Head	1.05
U	U-Tube Bundle	0.90

Table 2: Correction factor for rear head types.

engineered product is impacted significantly by decisions made at the design phases. While this influence decreases though all phases of the life cycle, the committed costs increase. It is seen that a commonly adopted approach of variant cost estimation based only on geometric information of the component is not always accurate. Traditional cost estimating methods for the different phases of a project can be observed in the literature, including: traditional detailed breakdown cost estimation; simplified breakdown cost estimation; cost estimation based on cost functions; activity based cost estimation; cost index method; and expert systems. While traditional cost estimating makes use of blueprints and specifications, comparative cost estimating assumes a linear relationship between the final cost and the basic design variables of the project. By the emergence of Artificial Intelligence (AI) tools (i.e., neural networks) possible multi- and non-linear relationships can now be investigated.

Several authors have concluded that the area of the exchanger bears a strong relation to the total cost and while it considerably impacts the cost, therefore, the estimation of the cost of purchase is usually based on estimations of the heat transfer surface, and on earlier knowledge and experience of exchanger manufacturing. In addition, the shell diameter and tube diameter also become important factors influencing directly the area of the exchangers under development. At the other hand, the pitch and configuration of the bundle are also clearly important factors for the cost of the new heat exchanger. Finally, the heat exchanger type is identified as one of the main key parameters; Types of the exchanger are classified by

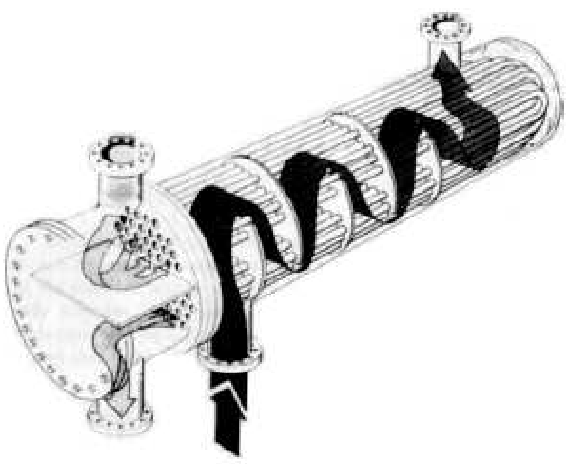

Figure 1: Typical shell and tube heat exchanger with shell side fluid flow.

TEMA with a well-known nomenclature. Accordingly, a shell and tube exchanger is divided into three parts: the front end, the shell, and the rear head. Please refer to reference [3] for more details on Shell and tube heat exchangers. We use correction factors related to front or stationary head type (f) and rear head type (r) as factors that represent the heat exchanger type. Tables 1 and 2 show the correction factors f and r respectively. Finally the cost per area can be expressed as a function of tube pitch (Pi), f and r factors and shell and tube diameters (Dsi and do, respectively).

3 Methodology

The main hypothesis of this research is that by using neural networks based techniques is possible to develop costs estimation models for shell and tube exchangers during early design stages in a make to order production scenario. Through experimentation using simulated data these models will be used to provide answer to the following research questions:

- Is possible estimate the product costs using soft computing methods?
- Incomplete information is an impediment to effective product costs estimations?
- A very small set of product characteristics can be used for cost estimation using soft computing based methods?

A case of shell and tube heat exchangers was simulated using data based on a cost function. In this simulation, it was pretended that a company wanted to estimate the cost of a new heat exchanger in its conceptual design stage. The experiment presupposed that product costs of all similar exchangers follow the same single cost function, so that costs are completely determined by the product attributes known at the time of cost estimation. Information about heat exchangers provided by different manufacturers and designers was used for construct plausible cost function. This function was used to generate training and test data. function. Situating the simulations at an early phase of development, only six attributes about the product in question are available. Table 3 depicts the attributes and their value ranges for all simulations. Training and testing data for all simulations were generated with randomly chosen input values. Neural networks were then applied to these data, and it was tested how well they were able to fit the underlying cost function.

Design Parameter	Parameter Definition	Parameter Range
x1: Pi	Tube Pitch(in)	0.40-2.00
x2: Dsi	Shell diameter(mm)	10.0-150
x3: do	Tube diameter (mm)	0.60-2.00
x4: r	Rear head factor	0.80-1.50
x5: f	Stationary head factor	1.00-1.60

Table 3: Design parameters for the input layer of the ANN tested

A set of configurations of neural networks for cost estimation during early design stages in a make to order production scenario were defined and tested. The performance of the different configurations and training strategies used in this research were compared and tested. In a number of experiments, neural networks were trained and applied to a set of case data. The accuracy of the cost estimation results and other indicators of performance were explored. The experiments were made up according to the following strategy: training and test data for the experiments were generated by the MonteCarlo method ascertaining that they follow a given cost function. In this simulation, a hypothetical company wants to estimate the cost of a new heat exchanger during its conceptual design stage. The experiment presuppose that product costs follow the same single cost function, so that product costs are completely determined by the product attributes totally or partially known at the time of cost estimation. Once the data be generated by the simulation experiment, alternatives of configuration of neural networks were then applied to these data, and tested how well they were able to fit the underlying cost function. Therefore, several sensibility experiments were carried out for testing the correlation degrees of the parameters included in the models. The neural network modeling phase corresponds to a complex and dynamic process that requires the determination of the internal structure (i.e., the number of hidden layers and neurons and the type of activation functions, plus the learning algorithm for training phase). Usually, the number of processing elements and hidden

Test Number	Training Set Size	Testing Set Size	Number of neurons/layer
1	200	100	4,4,1
2	100	100	10,20,1
3	50	100	10,20,1
4	200	100	10,20,1
5	200	100	10,10,1
6	200	100	10,1
7	100	100	4,4,1
8	100	200	10,10,1
9	100	100	10,1
10	50	100	4,4,1
11	50	100	10,10,1
12	50	100	10,1

Table 4: Alternative configurations of tested ANN.

Test Number	CPE %
2	75,38
11	69,6
3	68,49
12	67,87
7	64,15
8	57,91
10	57,78
9	48,91
1	20,45
4	20,45
6	5,32
5	5,31

Table 5: Results obtained in test runs

layers are determined by trials, since there is no rule to determine it. Therefore, the neural network model were determined empirically, rather than theoretically derived. With regard to the specific neural architecture used, the multilayer perceptron (MLP) has been preferred, since it usually leads to the most satisfactory results. The proper structure has been selected after having tested more ANN configurations with different numbers of hidden layers, different numbers of neurons for each level, and different inter-unit connection mechanisms as illustrated in table 1.

The models performance is measured by using the cost percentage error (CPE) formula (Eq. (1)):

$$CPE = \frac{E(i) - T(i)}{T(i)} * 100\% \tag{1}$$

Where E(i) is the model output, T(i) is the target output. The results of the testing phase are reported in Table 5.

In addition, some comparison between actual costs versus predicted costs were performed. Figure 2 shows the

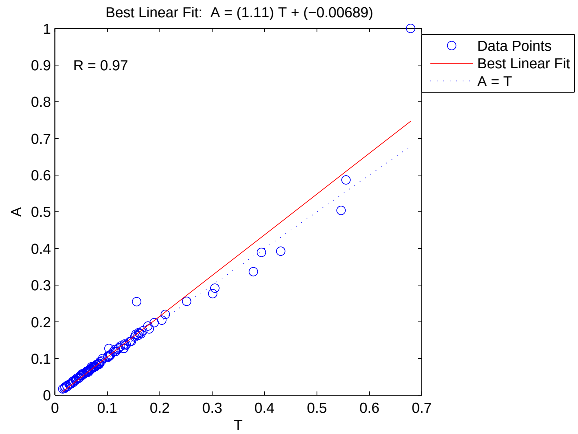

Figure 2: Comparison between test data and output data as scatterplot.

scatterplot of actual versus predicted costs for experiment 5. It is seen that most of the points lie very close to the line for strong prediction. For perfect prediction, all points should lie on this line. Hence, this chart provides the linear equation of the regression line (in the form of Y=Ax+B) between predicted and actual values. In this equation the closer to 0 is the B factor and the closer to 1 is the slope of the line (A factor), the better can be considered the estimation. The model number 5 has been selected. The configuration of the neural network include an input layer of 5 neurons corresponding to the five input parameters and an output layer of one neuron as the target (cost per exchange area). Two hidden layers both with 10 neurons. The input parameters (design variables and predominant cost drivers) for the input layer are presented in Table 1. The learning algorithm selected corresponds to Levenberg-Marquardt and the transfer function is logsig. Figure 3 plots the comparisons between simulated and real values of the testing set. Note that the determination coefficient R^2 is equal to 0,94 and the correlation coefficient (R) is equal to 0,97.

4 Conclusions

A neural network based model has been developed for early cost estimation of shell and tube heat exchangers by applying the principles of supervised learning of neural networks. This model proved that neural networks are capable of reducing uncertainties related to the cost estimation of a shell and tube heat exchangers. The use of cost estimation predictive models in the first stages of the highly product development process is of fundamental importance to start of the cost management process and influences the 'go/ no go' decisions. The anticipated knowledge of cause-effect relationships between design solutions and the production costs is extremely useful both for internal manufacturing activities, and for purchased parts. Through the Artificial Neural Networks approach

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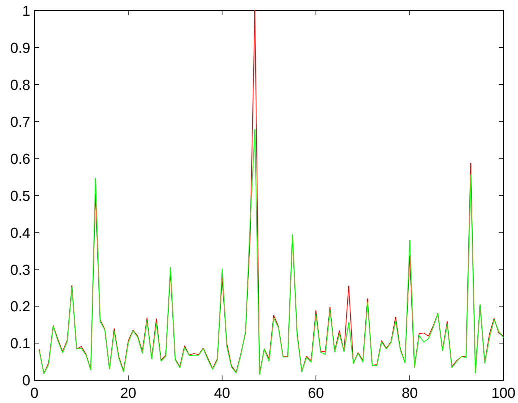

Figure 3: Comparison between test data and output data.

the possibility of building a full-scale knowledge-based model for predicting the total cost of heat exchangers is broaden. This approach solves the complex non-linear mapping for predicting the total heat exchanger cost at any phase of the design process.

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