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Parametric vs. neural network models for the estimation of production costs: A case study in the automotive industry ☆

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Abstract

This paper aims at illustrating 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. The results seem to confirm the validity of the neural network theory in this application field, but not a clear superiority with respect to the more "traditional" parametric approach: in particular, the ANN seems to be characterised by a better trade-off between precision and cost of development, while a critical point—especially in the specific application context—is represented by the reduced possibility of interpreting output data (which is critical for the "optimisation" of design solutions during the new product development process).

Keywords: Cost estimation; Parametric models; Artificial neural networks; New product development process; Target costing

1. Introduction

The estimation of future production costs is a key factor in determining the overall performance of a new product development (NPD) process: the earlier this information is known, the better the trade-off between costs and product performances will be managed.

Typically, the cost per unit of a given finished good is the sum of different kind of resources—raw materials, components, energy, machinery, plants, etc.—and the quantification of the use of each resource is extremely difficult in the first stages of the life cycle (and particularly in the early phases of the product development process), given the reduced amount of information and the low level of definition of the project.

However, it is just in these phases that the availability of the estimated production cost data is crucial, since most of the costs that will be sustained in the following stages are implicitly determined by the choices made during the elaboration of the concept and the detailed design of the new product.

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For this reason, different techniques and approaches have been developed to cope with the problem of the estimation of manufacturing costs in highly uncertain contexts. In particular, this article shows the results of a study aimed at comparing the results of the application of two of these techniques: the parametric approach (perhaps the most diffused in practice) and a predictive model based on the neural networks theory, which has known great diffusion in the last years in very different application contexts.

This paper has a further seven sections. The following one (Section 2) deals with the strategic relevance of cost management in the modern competitive scenarios, Section 3 consists of a brief review of the main cost estimation approaches that can be found in literature, while Section 4 illustrates the basic theoretical elements of artificial neural networks (ANNs). The remaining four sections are devoted to the illustration of the case study: in particular, Section 5 describes the application context (the characteristics of the firm, of the product and of production technologies), while the following illustrates the design, development and refinement phases of the two models. The quantitative and qualitative comparison of the results is contained in Section 7, while the last section is devoted to the conclusions.

2. The strategic relevance of the cost variable in the new product development process

The ever growing competitive pressures that characterise most sectors force firms to develop business strategies based on a large number of differentiation factors: higher quality and service levels, as well as customisation and continuous innovation must be made compatible with lower costs for firms to stay competitive in the market and be profitable.

The research of organisational, technological and managerial solutions and tools that can shift the trade-off frontier between costs and differentiation is then of fundamental importance in these contexts. In this perspective, a great step forward comes from the attention that has been given to the ''process view'' in all the managerial and organisational disciplines: the development of the theory of ''management by processes'' has led to the gradual elimination of functional barriers. In firms that adopt this approach, each functional manager is made responsible not only for the results of his unit, but also on the overall effectiveness of the processes in which his unit is involved, according to an input–output logic which is typical of the process view (Berliner and Brimson, 1988; Zeleny, 1988; Hammer and Stanton, 1999).

Of course, this process re-orientation requires a radical cultural change to be effectively implemented, and must be supported by an *ad hoc* re-engineering of the organisational structure and of the management control systems, with particular regard to the performance measurement systems.

In particular, the R&D department is one of the areas most involved in this process of organisational change. Being constituted mainly by people with technical or scientific competencies, during the new product development (NPD) process this unit traditionally puts much more emphasis on the technologically innovative contents and on the absolute performance of the product, than on the impact of the adopted solutions on the economics and on related figures (like the manufacturing costs or the contribution margin generated by the new product). In this sense, the process view of the firm can be of great help in making designers and product engineers more aware of the critical role played in determining the overall economic performance of the firm, as proved by the ''life cycle costing'' theory (Blanchard, 1979; Fabrycky, 1991; Shields and Young, 1991).

Indeed, the life cycle theory states that, although the great majority of costs of a finished good are generated in the manufacturing/distribution stage (given also the repetitive nature of these activities for almost all kind of products), most of these costs are implicitly determined in the early phases of development. In Fig. 1, this is shown by the different profile of the ''actual costs'' and of the ''committed costs'' curves: the latter is built ''translating'' the costs occurred in the various stages of the life cycle back to the instant in which the different decisional processes that implicitly fixed those costs took place.

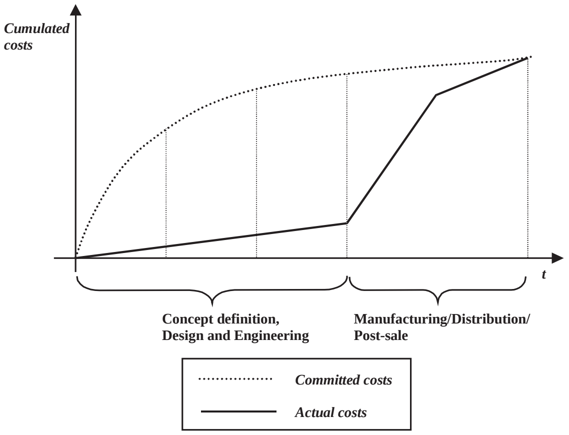

Fig. 1. Committed costs and actual costs along the life cycle of a product.

These considerations have led to the development of design rules and techniques, whose objective is to help engineers and designers in their decisional processes and make them aware of the implications of the alternative design solutions on the future costs of the product (Ulrich and Eppinger, 1995).

These approaches can be named differently, according to the specific application context and the emphasis given to the economic figures (Huang, 1996):

- *Design for manufacturing/assembly*: design rules finalised to the standardisation of components and to the simplification of the production processes (either fabrication or assembly processes).
- *(Re-)design to cost*: while the rules included in the previous category can be rather generic and qualitative in nature, this approach is usually more structured and analytical: indeed, its aim is the quantification of the economic impact of the different design solutions adopted[1].
- *Target costing*: this management theory changes in a quite radical way the approach to the development of a new product (Hiromoto, 1988; Sakurai, 1989; Ansari et al., 1997; Cooper, 1997); while in the "traditional" process the economic-financial evaluation is conducted only after the concept definition phase (if not later), according to the target costing philosophy (particularly diffused in Japan automotive industry) the starting point consists in the determination of the estimated market price of the new product. This information, coupled with the expected (desired) profitability margin, leads to the identification of the sustainable production cost per unit. All the subsequent design and development phases must then be "cost" driven (i.e., all decisions must be made according to the final objective of meeting the target production cost). The overall production cost is then divided into its components and "second level" target costs are then identified for all purchased parts and for internal conversion activities: in particular, the target purchase costs are discussed with all the suppliers, in a rather classical bargaining approach aimed at price reduction.

All these managerial approaches highlight the strategic relevance of the information regarding the future manufacturing cost of the product (or of its components): in the life cycle theory the overall objective resides on the minimisation of the cumulated life cycle cost. Hence, the first step consists in estimating the "occurred costs" curve (and, then, the manufacturing costs, which represent the most important element). Similarly, in a firm which adopts the target cost approach, the anticipated knowledge of the estimated future manufacturing costs is fundamental to understanding whether the target cost can really be reached or not (according to the gap between the target cost and the data resulting from the application of a cost estimation technique). Moreover, if an assembler firm can make reliable predictions about the production costs of its suppliers (for purchased components), its bargaining power will be higher due to the reduction of information asymmetry (Porter, 1980): this appears particularly critical in the target cost

[1] It must be noted that sometimes the term "redesign to cost" is used with a totally different meaning: it is referred to the redesign of business processes, and not of products, and includes all the organisational tools and rules aimed at the redesign of business processes in a cost-reduction perspective (someway similar to BPR theory).

approach, due to the "pressure" that is made on suppliers to meet the objective.

All these considerations justify the efforts that have been made in the field of cost estimation techniques in recent years. The next section is devoted to the illustration of the state of the art, with particular regard to the latest developments.

3. The cost estimation techniques

In literature, three main quantitative approaches can be identified for cost estimation purposes.

(a) *Analogy-based techniques*: these techniques belong to the category of qualitative estimation methods. They are based on the definition and analysis of the degree of similarity between the new product and another one, which has been (or is being) already produced by the firm. The underlying concept is to derive the estimation from actual information regarding real products. However, many problems exist in the application of this approach, due to:

- the difficulties in the operationalisation of the concept of "degree of similarity" (how to measure it?);
- the difficulty of incorporating in this parameter the effect of technological progress and of context factors.

This kind of techniques is mainly adopted in the first phase of the development process of a product, because it allows obtaining a rough but reliable estimation of the future costs involved.

(b) *Parametric models*: according to these techniques, the cost is expressed as an analytical function of a set of variables (so, they belong to the quantitative methods category). These usually consist in some features of the product (performances, morphological characteristics, type of materials used), which are supposed to influence mainly the final cost of the product (known also as "cost drivers"). These analytical functions are usually named "Cost Estimation Relationships" (CER), and are built through the application of statistical methodologies (see the NASA handbook on parametric cost estimating, for example). They can be adopted during the development of new products and as a control during the implementation, providing a target for the final cost of the product. Although they are mainly used for the estimation of the cost of large projects (such as in the aeronautical field), they could be effective also for the estimation of the cost of those products, where the cost drivers could be easily identified.

(c) *Engineering approaches*: 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, labour, 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.

These can be considered as "classical" approaches to cost estimation: passing from the first to the last the average precision of the methodology increases (and its cost too, of course). But it is also clear that the choice between the three methodologies is not completely free. Each of them is suited to different stages of the NPD process, given their different degree of analyticity and the different amount of input data needed.

4. Artificial neural networks for cost estimation

In the last years a new approach, based on the theory of ANNs, has grown in popularity. ANNs are inspired to the human brain functionality and structure, which can be represented as a network of densely interconnected elements called *neurons*. The connections between neurons are called *synapses* and could have different levels of electrical conductivity, which is referred to as the *weight* of the connection.

This network of neurons and synapses stores the knowledge in a "distributed" manner: the information is coded as an electrical impulse in the neurons and is stored by changing the weight (i.e. the conductivity) of the connections.

ANNs inherit the above-explained structure: they are composed of a large number of elaboration units (the neurons) linked via a weighted connections (the synapses). An ANN reacts to inputs by performing the sum of the weighted impulse of the neurons: the result activates one or more specific output neurons which provide the answer of the net.

Another similarity between ANNs and a brain is the learning approach. Like the human brain, an ANN needs to be *trained*, which means that it needs to store knowledge by means of the elaboration of a set of training data (also called *patterns*), which represent the experience "cumulated" by the ANN. This training campaign allows the network designer to "fine tune" the weight of the connections between neurons, by storing the specific knowledge included in the patterns.

Moreover, one of the most important characteristic of ANNs is their ability to infer from their knowledge the answer to questions (inputs) that they have never seen before. This is referred to as the *generalisation* ability of the ANNs. This feature of ANNs reduces the amount of data needed in the training phase.

To summarise, the ANNs represent a powerful, non-linear and parallel computing approach that could be used to perform fast and complex computations.

4.1. Multilayer ANNs

There are a multitudes of ANNs structures and different classification frameworks. For examples, ANNs could be classified according to the learning method or to the organisation of the neurons (see, for example, Chester, 1993).

The one that have been used in this work is called Multilayer Perceptron (MLP), in which neurons are organised in several layers: the first is the *input* layer (fed by a pattern of data), while the last is the *output* layer (which provides the answer to the presented pattern). Between input and output layers there could be several other *hidden* layers (see Fig. 2). The number of hidden layers has an important role in determining the generalisation ability of the MLP.

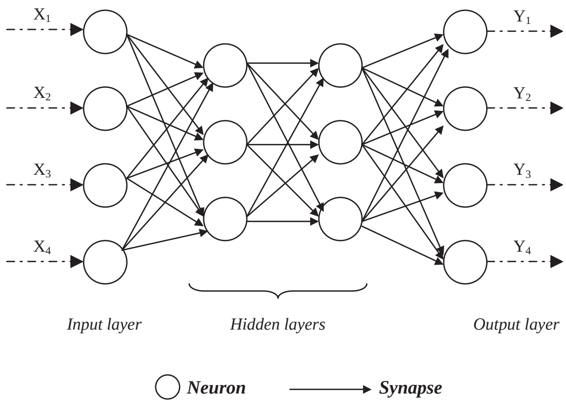

Fig. 2. The structure of an MLP.

MLP represents a tool, which is able to identify the relationships between different data sets, although the form of these relationships is not defined *ex ante*. For this reason they are called "universal regression tools" (Hornik et al., 1989).

4.2. Application of ANNs

This approach has known the first applications in the manufacturing sector for planning, emulation and management of production processes and plants. For example, Cavalieri and Taisch (1996) and Cavalieri et al. (1995, 1997) have developed ANNs for the design of hybrid intelligent systems and of process plants, while Zhang et al. (1996) illustrate the use of a neural network-based model for the estimation of the packaging cost, based on the geometrical characteristics of the packaged product (the so-called "feature based cost"). However, it must be underlined that the neural network theory has been applied in the most disparate sectors: for example, O'Rourke (1998) deals with neural networks for the estimation of the market value of equity stocks, and concludes that the results achieved are better than those of a linear predictive model.

5. The case study

The objective of the research was to compare the results achieved with the application of a traditional cost estimation technique with those obtained through the design and implementation of an *ad hoc* ANN.

Given the objectives and specific application context of the cost estimation methodology in the analysed firm, the preference among the "classical" methodologies has gone to the parametric model. In fact, the analogy-based approach has been judged as too approximate, while the engineering analysis was not applicable, since the cost of a purchased part (and the detailed specifics of the production process of the suppliers) were not known to the firm.

The interest for this kind of comparative analysis derives also from the still poor literature on this topic; indeed, the main references found are the following:

- an analysis of the results of the application of ANN vs. regression models for the determination of product costs in assembly industries (Shtub and Zimmermann, 1993);
- the work by Mason and Smith (1997), who compare the performances of regression and neural network approaches for cost estimation purposes. The results show that the ANN-based models are characterised by higher precision, especially when the analytical expression that links input and output variables is not known, or when it cannot be expressed in polynomial form.

The analysis was conducted through a real case study provided by an industrial company operating in the automotive sector.

The main mission of the company is the design, production and sale of braking components and integrated systems for civil and industrial vehicles, as well as for racing applications.

The customers are mainly very large industrial contractors (the major automotive multinational companies), which in the last decade have almost completely outsourced the production of braking components.

The high degree of competition that characterises the sector forces firms to search for differentiation elements; but at the same time, due to the relatively poor bargaining power (with respect to large customers) great attention is paid to price levels. Hence, one of the strategic objectives that have been identified by the company top management consists of the analysis and reduction of product costs (both purchasing costs of components and internal production and assembly costs).

In this context, the adoption of formal methodologies for the accurate estimation of manufacturing costs of new products has been considered of great importance in order to pursue the claimed strategic objective of the company.

In particular, this study focuses on the estimation of the production costs of *cast iron disk brakes*, which are then assembled with other components to produce braking systems, but can be also sold directly in the after market.

The overall production system of this typology of disk brakes is sketched out in Fig. 3. Two main production phases can be identified:

- *Foundry*, which produces raw disks starting from cast iron;
- *Mechanical manufacturing*, which produces the finished disks with the dimensional and surface features as specified in the project specifications. These disks are then assembled with other components in order to get a final disk braking system.

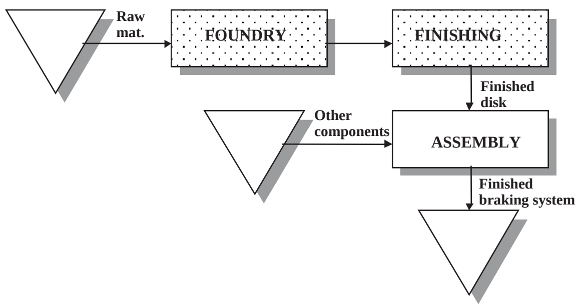

Fig. 3. The production process of a car braking disk.

The cost estimation modelling techniques can be used to quantify a reference cost value for the raw disk and the finished disk as well. It must be underlined that some of the production phases can be partially or totally outsourced: in particular, the foundry activities (which include the core preparation, melting and molding phases) are almost fully outsourced, and the same is happening also for the finishing stage. Hence, the availability of reliable cost estimation models is of fundamental importance both in the product development phase (totally internalised), and for the determination of the price of purchased parts.

6. The design of the parametric and neural models

The development of the two estimation techniques has been accomplished through the development of the design phases, which will be hereby described.

6.1. Problem definition and data collection

The first phase consisted in the clear definition of the project objectives and constraints. This aspect appears quite important in a company, which has recently re-engineered its internal organisation by moving from a functional structure to a more process-oriented view. Objectives, strategies and activities to be implemented must be accepted and shared by all the main actors of the product design process, which, in this case, were mainly constituted by product designers and those responsible for purchasing activities.

Once the problem and the methodology to be used had been defined, it was necessary to proceed to the analysis of product data, and to the identification of the information sources and of the corresponding business functions responsible for their maintenance and update.

In this case, the main typologies of data are:

- *Technological data*, related to the production processes.
- *Design data*, related to the morphological features of the product.
- *Cost data*, such as raw material costs, labour costs, etc.

Table 1
The identified cost drivers

Cost driver
Raw disk weight
Kind of material
Number and type of foundry cores
Type of disk
Geometric shape

The main sources of information were the Design and Engineering Department, the Procurement Department and the Accounting Department.

Table 1 reports the most meaningful cost drivers identified during the analysis of product data. One of the main characteristics of these drivers is their quite simple quantification even in the preliminary phases of the product development process, when only first raw design specifications are being assessed.

6.2. Data analysis and regression

Once the product cost drivers have been defined, it is necessary to evaluate the consistency of the available data, in terms of measurability, reliability and completeness (i.e. real information content). In particular, with regard to the last point, data could result in being not suitable or not sufficient for the purpose—which inevitably leads to recycles on the previous phases—or they could be redundant—which causes inefficiencies.

Measurability deals with the problem of assigning a range of values to each variable or driver. In the case of qualitative variables, this could imply the decomposition of the estimation problem, and, hence, the generation of several parametric models. This was the case of the variable "type of disk", whose values turned out to be the product families, according to the tree-like structure illustrated in Fig. 4.

A first level classification between traditional (full) and special disks, and the further subdivision

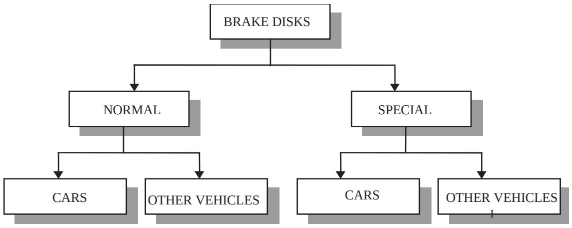

Fig. 4. The different families of brake disks in the case study.

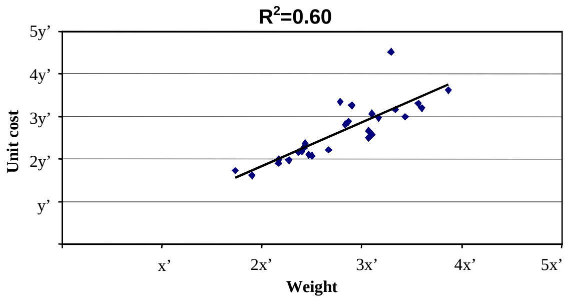

Fig. 5. The correlationship between weight and unit manufacturing cost of the different products.

in two different application fields (automotive and industrial sectors) led to the partition of the whole problem into four more consistent sub-problems, without loss of generality.

Once the statistical consistency of the sample set of data had been tested, statistical and linear regression models have been used to find out the one-to-one relationships between each of the selected cost drivers and the dependent variable (i.e. the product cost).

Fig. 5 shows the linear correlation between one of the cost drivers, the weight of the raw disk, and the product cost. As can be easily noticed both from the graph and by the analysis of the coefficient R^2, the information given by this simple model is quite significant. However, from a more thorough analysis of the figure it is quite evident that this simple regression model lacks robustness, due to the significant variances between some couples of data. Hence, the simple regression model so far illustrated must be completed by some other parameters to improve its performances.

6.3. The design of the parametric model

In order to complete the information provided by the linear regression model, a Cost Estimation Relationship (CER) has been developed, based on a regression model, as illustrated in Eq. (1):

$$C = \mathrm{FC} + \left(\mathrm{Cco\ Nco} + \frac{\mathrm{Crm\ TF}}{1 - \mathrm{SC}}\right) W, \tag{1}$$

where the meaning of the single terms of the model is reported in Table 2.

The analytical expression includes also three corrective factors, which are mainly due to the fact that foundry activities can be performed in different production systems (both internal and of third parties). More precisely:

- transformation of cast iron (TF): takes into account the different conversion costs sustained in the different plants for producing raw disks from cast iron;
- scrap rate (SC): represents the rate of scraps or wastes due to the characteristics of foundry operations (which can have a relevant impact on final costs);
- fixed cost (FC): is a corrective factor.

It must be underlined that, although this paper focuses on the illustration of the parametric model for foundry activities, the same approach has been applied also to the subsequent manufacturing phase, and led to the identification of the analytical function described in Eq. (2):

$$C = (C_{\mathrm{turn}} + \mathrm{Cm}_{\mathrm{mill}} + \mathrm{Cm}_{\mathrm{grnd}} + \mathrm{Cm}_{\mathrm{oil}} + \mathrm{Cm}_{\mathrm{balanc}} + \mathrm{Cm}_{\mathrm{ind}} + \mathrm{Pack} + \mathrm{Cg})\mathrm{Sh}. \tag{2}$$

Table 2
Parameters and coefficients in the foundry model

Term	Coeff./Param	Description
C	—	Unit cost of disk brake
FC	Coefficient	Fixed cost factor
Cco	Coefficient	Core cost (per kg of cast iron)
Nco	Parameter	Number of cores
Crm	Parameter	Unit cost of raw material (cast iron, €/Kg)
SC	Coefficient	Scrap rate (/100)
TF	Coefficient	Cast iron/steel conversion factor
W	Parameter	Weight

In this case, each term represents a component of the cost related to the execution of the different manufacturing operations (turning, milling, grinding, lubrication, balancing, etc.). Some of these variables turned out to be quite independent from the morphological characteristics of the disk, and they have been assigned mean values. Conversely, other variables are strongly affected by this parameter: it is the case of turning and milling operations, whose working time depends to a great extent on the geometric size of the disk.

The values of the coefficients of both models that have been assigned in order to minimise the mean absolute percentage error (MAPE) are defined in Eq. (3):

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{|\text{Estimated cost}_i - \text{Actual cost}_i|}{\text{Estimated cost}_i}100\right). \quad (3)$$

6.4. The design and training of the artificial neural network

In the discussed case, ANN represents a valid tool for the identification of the transfer function of the analysed processes, through an implicit link between the input value—the morphological and technological characteristics of the disk—and the output value—the cost.

With regard to the specific neural architecture used, given the peculiar purposes of the application, the multilayer perceptron (MLP) has been preferred, since it usually leads to the most satisfactory results, as reported in e.g. Hornik et al. (1989).

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 3.

The learning algorithm adopted is a typical one for this type of ANN: the backpropagation algorithm with momentum and a flat spot elimination term.

The set of patterns has been divided into two subsets: one has been used as a *training* set (in order to adjust the weight of the connections and store the knowledge) and the other one has been used as a *validation* set to evaluate the responses of the net to unseen patterns (in order to evaluate the degree of generalisation).

Table 3
Alternative configurations of ANN

ANN	Number of neurons per layer	
	Hidden layer 1	Hidden layer 2
1	3	0
2	5	0
3	7	0
4	9	0
5	3	5
6	5	3
7	5	4
8	6	3

The results of this testing phase are reported in Fig. 6: the performance indicators used are the MAPE and the Generalisation factor (Gf), which is defined as

$$\text{Gf} = \frac{k}{n}100, \quad (4)$$

where n is the number of patterns that compose the validation set and k is the number of such patterns estimated with an error less then 5% (this value having been fixed as a threshold level).

It is quite evident that the two-layer configuration shows better performances than the one-layer one. This result is a further confirmation of some theoretical assumptions reported in literature (Chester, 1993), where the superiority of a two-layer solution is put in relationship with its shorter training times (given the same number of connections) and the better rate of output prediction.

7. Comparison of the results of the two approaches

The parametric and ANN models have been tested and validated by comparing the results provided by these models with the actual costs of the twenty most relevant components (raw disks) purchased or manufactured by the firm (the

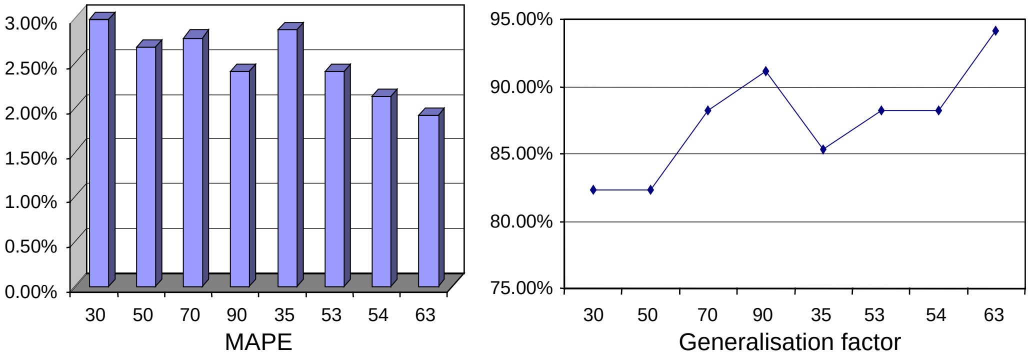

Fig. 6. The estimation error and the generalisation factor.

relevance being calculated in terms of incidence of sales).

The statistical analyses showed the superiority of the parametric model with respect to the simple regression line: the average MAPE fell from 15% to about 6%. But the different releases of the neural network registered even better performances. This outcome can be easily seen in Fig. 7, which shows the average MAPE of the estimated production costs of the different part numbers (aggregated by production plant).

Similarly, Fig. 8 shows the compared estimation error of the two models on the twenty selected part numbers: the maximum value is about 15% for the parametric model, while the neural network never reaches the 10% threshold, and only in six cases is above 5%.

Of course, the superiority of the neural network could derive from a poor design of the parametric model (although this seems not to be the case of the analysed problem). But, apart from absolute superiority judgements, what emerges is the robustness of the ANN, which leads to excellent results on all of the validation samples, thus contradicting those who say that this methodology, thanks to its many free parameters, allows the error on data used for its construction to go to zero, while the overall performance (the mean error on the population in general) can be far less satisfactory (Mason and Smith, 1997)[2].

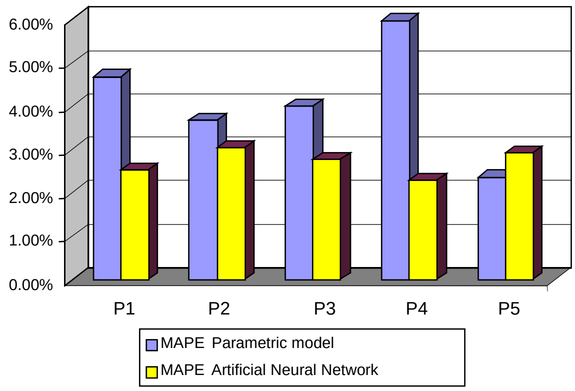

Fig. 7. The average estimation error of the two approaches (five plants).

But it is also interesting to extend the analysis beyond the quantitative data to include also some qualitative considerations.

The most relevant point concerns the inherent logic of the two approaches: while the use of a parametric model requires the specification of the analytical expression of the relationship that links input and output, this is not necessary with a neural network. Hence, the ANN is characterised by the possibility to determine autonomously the most appropriate form of the relationship. This

[2] This point is linked to the bias/variance problem examined by Geman et al. (1992), which is particularly critical in case of "resubstitution" validation method, where the construction set

(*footnote continued*)
is identical to the validation set. In this case, the model can be severely biased, as proved by Twomey and Smith (1993). Given their inherent characteristics, neural networks are supposed to be particularly affected by this problem (hence, the resubstitution validation method should be avoided).

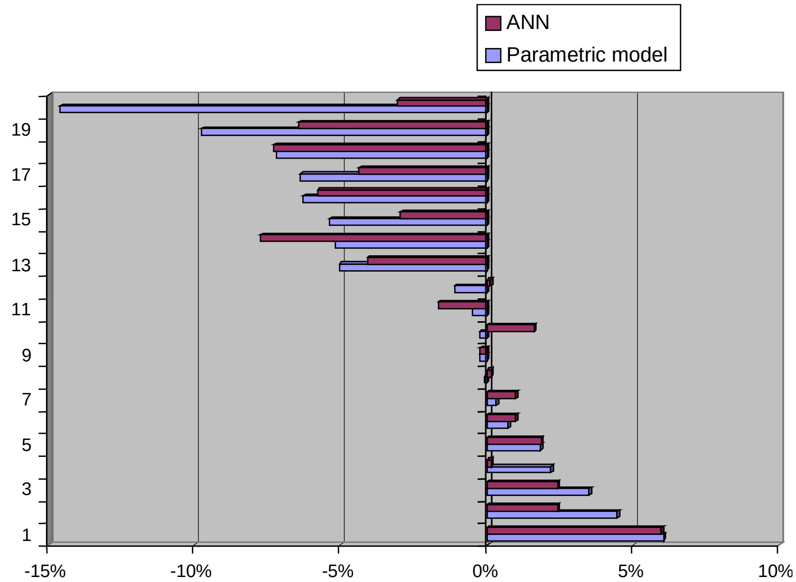

Fig. 8. The compared estimation error for the 20 selected components (percent values).

can be seen both as a strength and a weakness; indeed:

- the *ex ante* analysis of the problem is much leaner and faster, and in the case of very complex or innovative problems the outcome is not dependent on the ability of the analysts to find the key independent variables and the most appropriate kind of analytical expression;
- at the same time, the impossibility to know the kind of relationship can be seen as a limit of the neural network approach, since it is not clear how the results are achieved. In other terms, in the neural network approach the object of analysis is treated as a "black box"; hence, it is impossible to give a theoretical interpretation to the results provided by the tool, especially in the case of unpredicted or (at least intuitively) unjustified values. This fact has often led to some scepticism about this methodology in several application contexts, due also to the difficulty that its "sponsors" face when they are asked to prove the quality of the outcome in case of counterintuitive or questionable results.

Moreover, it could be objected that if the knowledge of the form of the relationship is not needed to implement a neural network approach, it is nevertheless necessary to pre-determine the structure of the network. The answers that can be given to this critical consideration are the following:

- the application contexts of the network structures that have been developed so far (multilayer, Adaptive Resonance Theory or ART, self-organising, etc.) are quite well known, and the identification of the most appropriate structure is then facilitated;
- the software packages for the design of neural networks are generally provided with tools aimed at evaluating the "learning attitude" of the network, and, in case of negative response, at implementing the appropriate modifications.

Another point that is often cited by the users of parametric models is the excellent (or at least satisfactory) quality/ cost ratio. But the implementation cost of a neural network is generally quite similar to that of a parametric model (the lower costs of preliminary analyses being balanced by the higher costs of developing and testing the ANN). Instead, the higher robustness of the methodology, and the consequent higher propensity to deal with redundant or wrong information enable the elimination or consistent reduction of the activities of data analysis, which are generally very time consuming (and, hence, quite expensive).

Another strength of neural networks is related to their flexibility to changes made in the structure of the analysed system once the development of the model has been already completed. For example, if the production process of the firm is modified through the implementation of new technologies, while the parametric model must be completely revised and re-tested, using a neural network it will be sufficient to conduct a new training program with a new set of data (the structure of the network may not even be modified).

On the other hand, neural networks are completely data-driven: an adequate set of construction data is then required, while a CER for a parametric model can be also deduced from technical considerations on the production process and on the kind of resources used (as for the typical engineering estimating approach), provided that it can be subsequently validated.

8. Conclusions

The use of cost estimation predictive models in the first stages of the product development process is of fundamental importance to "optimise" the concept of the new product according to the firm's overall competitive strategy and key success factors. 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.

The choice of the predictive model is generally based on the classical cost/ benefit ratio: in this sense, the regression models have often been preferred. But the more recently developed ANNs seem to represent a valid alternative, especially when the CER form is not known, and cannot be logically argued (since in this case psychological barriers deriving from the impossibility to check the relationship with common sense can be overcome more easily). In the case study illustrated in this paper, with respect to a parametric model the ANN has shown better results in all the validation samples, and no significant variance problems (i.e. the dependence of the model on the data set used to construct it) have emerged.

Anyway, to foster the diffusion of this methodology it is necessary to make it more "transparent" to the analyst, by developing software tools which reproduce in a comprehensible, easy-to-use way the behaviour of the network.

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