The Model of Raw and Packaging Materials Cost Estimation Using Neural Networks

Jasna Gamulin
University of Zagreb, School of Medicine
10000 Zagreb, Croatia
jasna.gamulin@gmail.com

Abstract. *Raw and packaging materials cost estimation is a regular procedure in purchasing departments. The process of cost estimation in the „classical“, iterative way is time consuming and demanding. In this paper a model has been developed in order to predict raw and packaging materials cost. The model is using the technique of neural networks (Neural Networks - NN). The result achieved by using the model is compared to prices actually realized in a given period and also to prices estimated in a classical way. The comparison of the prices showed encouraging results.*

Keywords. Cost estimation, neural networks

1 Introduction

The cost estimation process is a regular process taking place each year in purchasing departments and it is a part of a company planning process. Annual planning starts with estimating the sales i.e. estimating the demand for products the company is producing. The sales plan is than elaborated through the Material Resource Planning system (MRP) to exact total quantity of each raw and packaging material item needed for the finished product. Based on such an annual balance-sheet of needed materials, a purchasing professional is estimating the purchasing prices and additional purchasing costs for each specific raw material for the next year. The procedure is usually called “plan prices making”.

Plan prices and plan quantities give us the costs estimation for raw materials for the next year. The procedure is very important for the company since the estimation precision for each plan price directly influences the overall costs estimation precision. The estimation is based on knowledge and experience of the purchasing professional and a help in the process are the data on realized quantities and prices in the current year, raw-material market cognition, energy and raw-materials market trends, plan exchange rate for Croatian kuna for the next year, knowing the planned customs tariff changes, changes in customs quotas for specific product groups and special customs procedures (for example “import for export procedure”). Since the raw material is purchased both from domestic and foreign market, in a case of plan prices making for the purchasing from foreign market the price is planned in the specific currency and also the additional costs are planned (rate of duty, customs duty per quantitative unit of product, freight, forwarding agent’s fee, the costs of sanitary, market and phytopathological inspection).

For the medium size company producing approximately 50 products the number of items that should be purchased amounts from 500 to

1000. That is the reason why the process of cost estimation in the „classical“, iterative way is so time consuming and demanding. Plan prices making procedure using neural networks could be used as an auxiliary method when a quick estimation of budget for the next year or for a certain number of years is required.

2 Literature review

Kumar and Ganguli [4] described the iterative approach to raw materials cost estimation when buyers give their costs estimation which is then corrected or approved by commodity managers and finally confirmed by the director of Supply and Logistics. The whole procedure is repeated until the satisfying result is achieved. It is the way of raw materials cost estimation in well organized companies. The precision in costs estimation is very important for the appropriate decision making. Improving cost estimation is a critical part of inventory management process [2].

While it is widely accepted that a perfect estimate is not possible and even the best possible estimate will always contain a number of key risks, the goal of the forecaster is a practicable level of accuracy [7]. The regression analysis and neural networks are modeling techniques, identified by S. Newton [6] which have been used to develop models to estimate the cost of buildings. However, predominantly, these models rely on the use of historic (but recent) cost data. Elhag, T.M.S. i Boussabaine A. [1] modeled construction tender price estimation using artificial neural networks.

Lowe, D. J., Emsley, M. W. i Harding [5] described the development of linear regression models to predict the construction cost of buildings. Šimunović K. et al. [8 and 9] used artificial neural networks for inventory classification also recognizing the importance of inventory control being part of supply and logistic process.

3 Methodology

3.1 Neural networks (NN)

The idea of neural networks comes from neuropsychology where a nerve cell functioning principle has been used in order to develop the mathematical model. The basic unit of the model has been designed according to biological raw model. Basic learning principles of a neural network are associations between experimental samples [3].

In this paper the supervised learning will be applied where the differences between the desired and real sample output are eliminated by error back propagation model. The neural networks error back propagation model is usually used also for prediction. When using the error back propagation model for non temporal prediction, the number of prediction variables in numerical format assigns the number of input neurons while output neuron presents the prediction variable.

During the process of learning neural network error back propagation model is going through each specific case seeking to minimize the total error of the model and correcting the weight coefficients in the model. The chosen architecture of the neural network could be changed during the neural network training process by increasing the number of neurons in the input, output or hidden layer or by increasing the number of hidden layers of the neural network. Redesign of the neural network architecture is a heuristic process which could take place during the process of learning induced by poor learning results of the model. Reliability of the model is verified using test data and afterwards the analyst is estimating the degree of model reliability depending on error degree on test results [3].

The software used was Matlab R2009b.

3.2 Raw-material cost estimation model

Since each price is depending on a number of factors of which there are no quantified data in the company, the fluctuation of those factors has the attribute of randomness for the purpose of this model.

For instance, when purchasing for company the price of sugar is depending on sugar stock-market prices, EU (European Union) import and export quotas, The Republic of Croatia import and export quotas with EU and WTO (World Trade Organization), import customs duty per quantitative unit of product, the application of “import for export” procedure, freight, forwarding and warehousing charges, sanitary and market inspections charges, weather conditions for sugar beet cultivation, Croatian kuna exchange rate and finally it depends on negotiation with potential suppliers. As an illustration, the price of the foil used to pack the finished products depends also on the rate of duty, freight, forwarding and warehousing charges, sanitary and market inspections charges. The predominant influence to the price of the foil has the stock-market prices of aluminum, polyethylene and polyester and the costs of possible packaging material redesign (graphic preparation costs, costs of copper printing cylinders, costs of the possible writing off the unused old printed foil). Indeed, depending on the nature of each specific material there is a huge diversity of influences affecting the prices.

The aim of this paper is to develop the model of raw and packaging materials cost estimation (plan prices making) using neural networks.

The input variables of the model are:

- realized (purchased) quantities of raw and packaging materials in six years period
- realized raw and packaging materials prices in six years period

Output variable:

- prices planned for the seventh year

The variables are chosen according to the expert knowledge of purchasing professionals and working experience of many years in purchasing. It has been noticed that for the prices estimation most helpful are the data of previously realized quantities and prices. For the seventh year there are also the data available of real planned prices made in “classical” way, i.e. made by iterative planning procedure based on expert knowledge of buyers, commodity managers and logistics manager. The data of realized prices during the seventh year are available as well. Results achieved by described estimation model are compared to the data planned in the classical way and also to the data realized during the same year. The analysis is repeated for the raw-material without the packaging material. Since the raw material and packaging material have their own, different nature, the assumption is that the cost estimation model will do better with the plan prices making for the raw material. The reason for this assumption is based on experience. It is well known that raw material prices in food industry vary considerably less than packaging material prices and also the list of ingredients of the finished product does not change so often. This implies that the list of raw material codes is almost the same throughout the period of ten years or more and almost each code has history long enough for quality training of the neural network. Packaging material costs are meanwhile ascending year after year because of the more and more demanding market and packaging material items are continually redesigned or submitted to text changes. The fact that packaging material is changing in such a brisk manner is not contributing to the idea of prices planning using neural networks, since the history of a certain code (packaging material item) is too short. The problem could be solved by introducing the idea of descending codes. It means that when opening a new packaging material code, the substituted code would also be recorded and, if needed, the new code and the old code could be connected. The introduction of completely new products containing raw and packaging material not used so far, at this point needs to be completely excluded from the model.

The premises of the model are as follows:

- during planning period there will be no new material codes introduction
- the structure of the price is not of our interest (invoice price, forwarder, freight, insurance, additional printing costs).

4 Results

For the network training in the first case the data on realized prices and quantities of raw and packaging material during the six years period have been used. Only material codes with “history” have been taken into consideration which means only codes with data available for the whole period of seven years. Materials with only partial data available are excluded from

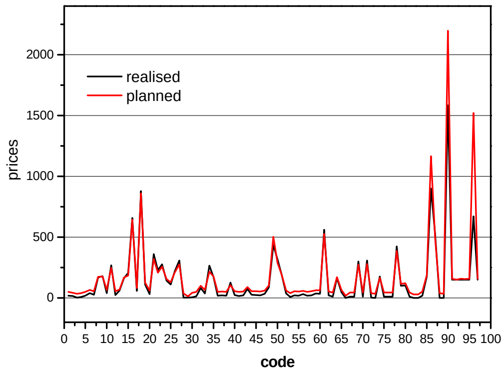

Figure 1: The comparison of prices realized during the seventh year and the prices planned using neural networks with 20 neurons in hidden layer, N=97 item codes

analysis. This premise limits the analysis to 57% of the totally purchased material value in the seventh year. Out of that, the analysis covers 81% of purchased raw material value and only 10% of purchased packaging material value. The first network training trial was with 20 neurons in the hidden layer. The comparison between realized prices during seventh year and the prices planned using neural networks is displayed on Fig. 1.

The next network training trial was with 50 neurons in the hidden layer and the result achieved is much better as shown on Fig. 2. Trials with even larger number of neurons in the hidden layer have led to the overfitting. The overfitting appears when networks with growing number of neurons in the hidden layer fit to the data almost perfectly but the foresight possibility aggravates.

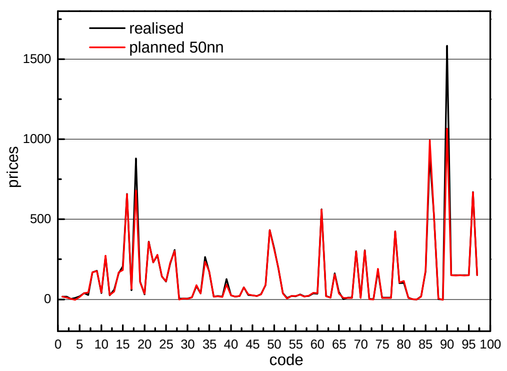

Figure 2: The comparison of prices realized during the seventh year and the prices planned using neural networks with 50 neurons in hidden layer, N=97 item codes

For the chosen segment of materials (97 items out of possible 445 items), the total realized value during the seventh year is equal to 44.467.054 kn (Table 1). Totally realized value in the 7th year for the codes with "history" is calculated as prices realized in the 7th year multiplied by quantities realized in the 7th year. In consideration have been taken only material codes with "history", it means only codes with data available for the whole period of seven years.

The value planned using neural networks is calculated by multiplying the realized quantities and prices planned using neural networks. In consideration have been taken only material codes with "history", it means only codes with data available for the whole period of seven years. The value of planned material costs calculated as described is 40.915.501 kn. Therefore, the budget planned for the seventh year using neural network vary from the realized budget for the same segment for approximately 8%. Material value planned in the "classical" way for the 7th year is calculated as prices planned for the 7th year in the "classical" way multiplied by quantities realized in the 7th year. In consideration have been taken only material codes with "history", it means only codes with data available for the whole period of seven years.

Table 1 indicates that the budget planned for the seventh year using classical, iterative procedure in the purchasing department for the same segment of materials is equal to 47.640.809 kn. Therefore, the budget planned by classical, iterative procedure applying the expert knowledge, varies from the budget realized for the same segment of materials approximately 7%. Fig. 3 displays the comparison of prices

Table 1: The survey of realized and planned values and item codes in the seventh year

Totally realized value (000) kn					From totally realized	Material value planned using (000 kn)			
Materials	**Totally realized**	**%**	**Codes with "history"**	**%**	**%**	**Neural networks**	**%**	**Classical method**	**%**
Raw	51 268	66	41 663	94	81	34 248	84	44 896	94
Packaging	26 859	34	2 804	6	10	6 668	16	2 745	6
Total	**78 127**	**100**	**44 467**	**100**	**57**	**40 916**	**100**	**47 641**	**100**
	Number of codes	**%**	**Number of codes**	**%**	**%**				
Raw	160	36	63	65	39				
Packaging	285	64	34	35	12				
Total	**445**	**100**	**97**	**100**	**22**				

realized during the seventh year and the prices planned in the classical way.

The neural network architecture is displayed on Fig. 4. The neural network consists from 3 layers, the input layer, the hidden and the output layer while the applied technique was back propagation. For creating the model 12 input variables were chosen, 50 neurons in the hidden layer and one output variable.

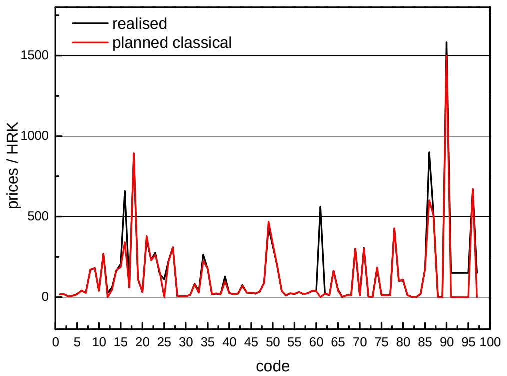

Figure 3: The comparison of the prices realized during the seventh year and the prices planned in the classical way, N=97 item codes

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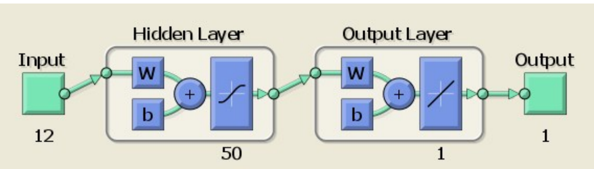

Figure 4: The neural network architecture

The neural network displayed on the Fig. 4 is trained using data from the period of six years. Training success results are displayed in the figure 5. It could be noticed that the network is successfully trained. The coefficient of correlation is very high and equals to r=0,99981. The network is then tested (r=0,94227) and validated (r=0,99001).

The next experimental step was to estimate material costs for the next year taking in consideration all material items i.e. also the items with incomplete "history" (the items with missing data for a certain part of the monitored period).

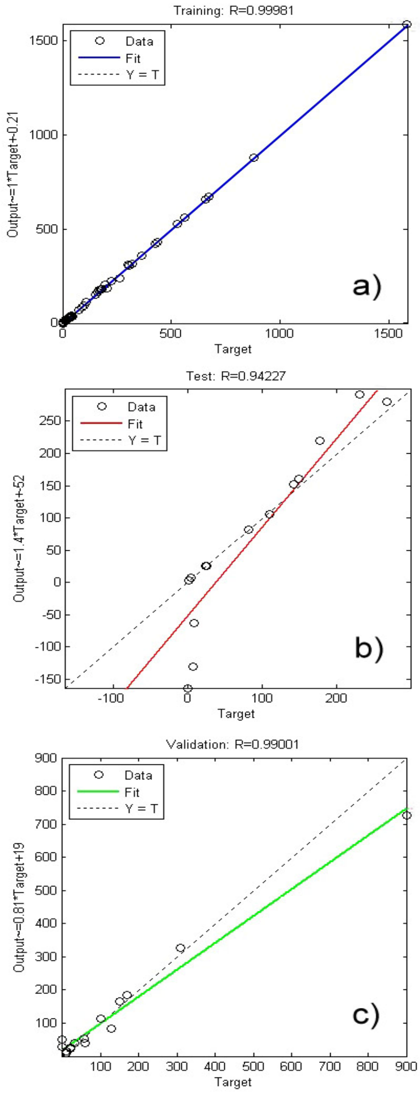

Figure 5: The neural network, data on realized quantities and prices during the period of six years, 50 neurons in the hidden layer, a) training r=0,99981, b)testing r=0,94227, c) validation r=0,99001

The network training was performed with 21,

Table 2: The survey of realized and planned values and item codes of raw material in the seventh year

Totally realized value (000) kn			From totally realized	Material value planned using (000 kn)	
	Totally realized	codes with data available at least in the 7th year	%	Neural networks	Classical method
Raw materials	51 268	34 877	68	33 882	37 930
	Number of codes	Number of codes	%		
Raw materials	160	76	48		

22 and 50 neurons but with the poor result. The sum of prices planned using neural networks differed from the sum of realized prices for 32% (50 neurons), 9% (21 neuron) and 8% (22 neurons). If the prices were weighted by realized quantities the deviation is even larger and the conclusion imposes that the described procedure is not bearing good enough result.

Finally, at the end of the experiment the cost estimation procedure is carried out only for raw materials. Only raw material codes with data available at least for the seventh year, it means also some codes with incomplete "history" have been taken into consideration. The number of codes was 80. Fig. 6 displays the comparison of prices realized for the chosen segment during the seventh year and the prices planned using neural networks with 25 neurons in hidden layer.

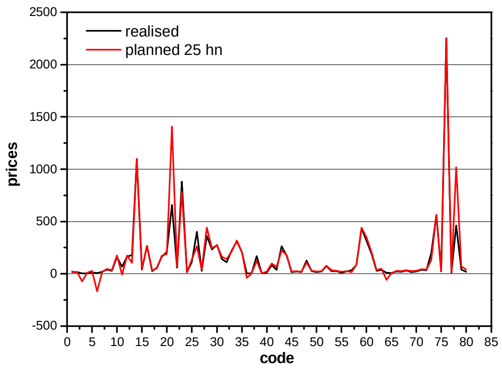

Figure 6: The comparison of prices realized during the seventh year and the prices planned using neural networks with 25 neurons in hidden layer. In consideration have been taken only raw material codes with data available at least for the seventh year, it means also some codes with incomplete "history", N=80 item codes

It could be visually perceived that the prices estimated using neural networks quite successfully follow the realized prices. Some prices showed a negative value which has no realistic meaning and those prices are removed from the obtained data. From the survey there have been removed 4 codes with negative value so that the total number of codes in survey remains 76.

For the chosen segment of materials (76 codes out of possible 160) the realized value in the seventh year is equal to 34.877.763 kn (Table 2). Totally realized value in the 7^{th} year is calculated as prices realized in the 7^{th} year multiplied by quantities realized in the 7^{th} year. In consideration have been taken only raw material codes with data available at least in the 7^{th} year.

The value planned using neural networks is calculated by multiplying the realized quantities and prices planned using neural networks. In consideration have been taken only raw material codes with data available at least in the 7^{th} year. The value of planned material costs calculated as described is 33.881.686 kn. Therefore, the budget planned for raw materials for the seventh year using neural network vary from the realized budget for the same segment approximately 3%.

Material value planned in the "classical" way for the 7^{th} is calculated as prices planned for the 7^{th} in the "classical" way multiplied by quantities realized in the 7^{th} year. In consideration have been taken only raw material codes with data available at least in the 7^{th} year. Table 2 indicates that the budget planned for the seventh year for raw materials using classical, iterative procedure in the purchasing department for the same segment of materials amounts to 37.929.638 kn. Therefore, the budget planned for raw materials by the classical, iterative procedure applying the expert knowledge, varies from the budget realized for the same segment of materials approximately 8%. Therefore, with a small intervention (removing the negative values) the prices estimation using neural networks achieves even better results than prices estimation using the usual, iterative procedure.

5 Conclusion

The model of raw and packaging materials cost estimation using neural networks could be very useful when the information of funds needed for purchasing materials for production in the forthcoming period is required on a short notice. Plan prices making in the usual way, taking place in purchasing departments should remain the part of a company's planning process since it expresses also the structure of funds needed (currency structure, additional costs structure) and since in case of huge market disturbances the expert knowledge of purchasing professionals is far more reliable having in mind that an artificial intelligence technique is "learning" from relatively short period.

The model already shows characteristics good enough for material costs estimation but the improvements are also possible. Introducing the idea of descending codes i.e. recording the connections between new codes and substituted codes, the longer “history” would be achieved for packaging materials and therefore equally good estimation possibility as for the raw materials. It is relatively small organizational change in a purchasing department contributing to easier planning by means of neural networks as well as planning in the usual way. Subject to the further research could be the elaboration of the model by introducing some new variables (currency exchange rate, GDP, oil prices). Further elaboration of the model could be also in the direction of cost structure estimation (currency structure, additional costs structure). The extension of the monitoring period of the realized prices and quantities is also contributing to better cost estimation using neural networks.

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