TRENDY EKONOMIKY A MANAGEMENTU
TRENDS ECONOMICS AND MANAGEMENT
ISSN 1802-8527 (Print) / ISSN 2336-6508 (Online)

2016 25(1): 48–55
DOI: http://dx.doi.org/10.13164/trends.2016.25.48

A Suitable Artificial Intelligence Model for Inventory Level Optimization

Tereza Šustrová

Abstract

Purpose of the article: To examine suitable methods of artificial neural networks and their application in business operations, specifically to the supply chain management. The article discusses construction of an artificial neural networks model that can be used to facilitate optimization of inventory level and thus improve the ordering system and inventory management. For the data analysis from the area of wholesale trade with connecting material is used.
Methodology/methods: Methods used in the paper consists especially of artificial neural networks and ANN-based modelling. For data analysis and preprocessing, MS Office Excel software is used. As an instrument for neural network forecasting MathWorks MATLAB Neural Network Tool was used. Deductive quantitative methods for research are also used.
Scientific aim: The effort is directed at finding whether the method of prediction using artificial neural networks is suitable as a tool for enhancing the ordering system of an enterprise. The research also focuses on finding what architecture of the artificial neural networks model is the most suitable for subsequent prediction.
Findings: Artificial neural networks models can be used for inventory management and lot-sizing problem successfully. A network with the TRAINGDX training function and TANSIG transfer function and 6-8-1 architecture can be considered the most suitable for artificial neural network, as it shows the best results for subsequent prediction.
Conclusions: It can be concluded that the created model of artificial neural network can be successfully used for predicting order size and therefore for improving the order cycle of an enterprise. Conclusions resulting from the paper are beneficial for further research.

Keywords: lot-sizing problem, inventory management, artificial neural network

JEL Classification: C53, C45, L81

Introduction

In today's highly competitive environment characterized by high consumer's requirements for products with high quality, low profit margins and short delivery times, enterprises are forced to take advantage of every opportunity to optimize their business processes.

The issue of inventory management is considered to be one of the most important functions of manufacturing and business enterprises, which often have a big impact on their overall performance. Usually it is necessary to consider a trade-off between high holding costs on one hand and poor service and high shortage costs resulting from low inventory levels on the other. The required solution lies in a suitable inventory management which ensures a satisfactory service level without keeping unnecessarily large stocks causing high expenses.

The paper presents the effectivity inquiry of artificial neural network modelling and forecasting in the issues of inventory management, especially in the lot-sizing problem. Several types of neural networks are created and tested within the research, searching for the most efficient neural network architecture. MS Office Excel was used for data analysis, preprocessing and standardization; MathWorks MATLAB Neural Network Tool was used for neural network forecasting.

1. Inventory management models and artificial neural networks

The purpose of the inventory management models is to provide an appropriate method for inventory regulation, mostly with regard to costs. So far no universal model for inventory management has been developed and a specific solution must be sought in each individual situation on the basis of the existing models.

EOQ model is frequently modified for various types of the required input data entry, such as in the case when rebate (a discount depending on the volume of the order for delivery) needs to be respected.

The first mathematical model for delivery size specification was the model developed by Ford W. Harris called Economic Order Quantity (Harris, 1913). This model is one of the single-product deterministic dynamic models and is the simplest model type – a model of periodically replenished inventory with constant delivery size. The assumption for the EOQ model is a single-level production process with no capacity constraints, which makes the problem become a single-item problem. The demand for that item is assumed to be stationary, *i.e.* demand occurs continuously with a constant rate. The EOQ model is a continuous time model with an infinite planning horizon. The optimal solution is easy to derive. The purpose of the model is to find the optimum size of a manufacturing supply which is the most economical for a manufacture. This means balancing of acquisition and storage costs.

Since the assumptions appear to be very restrictive and do not correspond to the practice in a vast majority of cases, more sophisticated models were developed in the latter half of the 20th century. First to mention is the economic lot scheduling problem (ELSP) where capacity restrictions come in (Rogers, 1958 and Elmaghraby, 1978). Because scarce resources are usually shared in common by several items, the ELSP is a single-level, multi-item problem. However, the ELSP still assumes stationary demand. It is a continuous time model too and the planning horizon is infinite again. Solving the ELSP optimally is NP-hard. Hence, heuristics dominate the area (Zipkin, 1991).

A quite different step was made from the EOQ model assumptions towards dynamic demand conditions. Wagner, Whitin (1958) created a so called Wagner-Whitin model which assumes a finite planning horizon which is subdivided into several discrete periods. Demand is given per period and may vary over time. However capacity limits are not considered which means that the single-level WW problem is a single-item problem. The solution is simple (Aggarwal *et al.*, 1993). Next model generations combined models with different capacity limitations and different dynamic approaches. The delivery size specification was extended with purchase planning (Drexl *et al.*, 1997).

A separate, later developed model type is the model with deteriorating goods. Deteriorating refers to the damage, spoilage, dryness, vaporization, *etc.* of the products. These models are also based on the classical EOQ model or the Wagner-Whitin model, subsequently modified for the required conditions. The basic typology is again derived from the demand nature and includes models with deterministic demand, time-varying demand, stock-dependent demand or price-dependent demand and also with stochastic demand. Special models are developed for the case of permissible delay in payment, including delay interest payment, purchase price discount and models including inflation and time value of money or inventory model with two warehouses (Goyal, Giri, 2001).

The study of various model situations, focus on simulating conditions, searching for outcomes, optimal solutions, and so on are among the most important current trends. For example, McNelis in his paper (McNelis, 2003) applies the neural network methodology to inflation forecasting in the Euro-area and the USA. There are many other research methods besides modelling, such as laboratory experiment (Gammisch, Balina, 2015), case study (Rudiene, 2014) *etc.*

The modeling of phenomena which arise from economic reality and are described by statistical data is possible thanks to methods based predominantly on branches of mathematics such as statistics, numerical methods, operational research, linear and dynamic programming, optimization, *etc.* (see, for example, Novotná (2012) or Novotná (2014)).

The study of various model situations, focus on simulating conditions, searching for outcomes, optimal solutions, and so on are among the most important current trends. The paper Ioana *et al.* (2010) presents a new concept for fuzzy logic in economic processes. In his paper Zhang (2012), investigated the sensitivity of estimated technical efficiency scores by different methods including the stochastic distance function frontier.

Artificial neural network models have been used to successfully solve the demand forecasting and production scheduling problem. In their paper, Gaafar, Choueiki (2000) applied a neural network model to a lot-sizing problem which is part of Material Requirements Planning (MRP) for the case of deterministic time-varying demand over a fixed planning horizon.

Paper presented by Megala, Jawahar (2006) addresses a dynamic lot sizing problem with capacity constraint and discount price structure. Two meta-heuristics, genetic algorithm and Hopfield neural network are designed for dynamic lot sizing problem. A computational study in paper shows that genetic algorithm is capable of producing adequate result whereas Hopfield neural network produces satisfactory results only for small size problems.

Aburto, Weber (2007) in their research presented a hybrid intelligent system combining Autoregressive Integrated Moving Average models and neural networks for demand forecasting. Study showed improvements in forecasting accuracy and proposed a replenishment system for a Chilean supermarket, which leads simultaneously to fewer sales failures and lower inventory levels.

Artificial neural network structure was also used and compared with traditional statistical methods by Hamzaçebi (2008). The results from the modeled artificial neural network utilized for time-series forecasting proved that the proposed ANN model comes with a lower prediction error than other methods.

Research introduced by Hachicha (2011) also uses artificial neural network and deals with the lot-sizing problem in supply chain by application of metamodelling simulation. The supply chain which is a subject of research operates in make-to-order environment (no possibility of stock keeping and limited production capacity) and is characterized by multi-product, multi stage, multi-location production planning with capacity constraints and stochastic parameters such as lot arrivals order, transit time, set-up time, processing time, *etc.* The results confirm the effectiveness, flexibility and usability of the artificial neural network method in practical applications.

Another artificial neural network-based model was developed by Paul, Azaeem (2011) which determines the optimum level of finished goods inventory as a function of product demand, setup, holding, and material costs. The model was tested with a manufacturing industry data and the results indicated that the model can be used to forecast finished goods inventory level in response to the model parameters. Overall, the model can be applied for optimization of finished goods inventory for any manufacturing enterprise.

A fast convergent BP neural network model for predicting inventory level is described in a paper by He (2013). The paper also applies the improved BP neural network model to predict the inventory level of an automotive parts company. The results show that the improved algorithm not only significantly exceeds the standard algorithm but also outperforms some other improved BP algorithms both on convergence rate and prediction accuracy.

We can summarize that soft computing methods can be successfully used in the area of inventory management and optimization. Developed models often showed robustness, high performance and gave a valid solution to the presented problem. Research of artificial neural networks confirmed their usability and effectiveness in practical application especially for solving the lot-sizing problem in production planning systems. Now we can concentrate on development of a soft computing methods-based model for solving the lot-sizing problem in business venture.

2. Artificial neural networks

Artificial neural networks are a branch of artificial intelligence. Multi-layer perceptron form one type of artificial neural network. We know also Single-layer perceptron ANN, Radial basis function networks or the whole group of Recurrent/feedback networks (Gardner *et al.*, 1998).

Artificial neural networks represent an analogy to human thinking, a simplified imitation of the principle of human brain. They are described as the black box with unknown inner structure and known outputs. Artificial neural networks usually work in two stages. In the first stage the network acts as an inexperienced man, learning to set its parameters to correspond to the required network topology. In the second stage the network already independently transforms inputs to outputs on the basis of knowledge obtained in the first stage. Each neural network consists of defined layers, input layers, hidden layers and output layers, and the learning method and the knowledge acquisition process.

Neural networks are appropriate in situations when chance plays a significant role in the process and deterministic relations are so complex and interwoven that they cannot be analysed and identified. They are therefore used for modelling of complex and irreversible strategic decisions where a network with more hidden layers is appropriate (Dostál, 2008, p. 42).

Some authors have recently focused a great part of their attention on the so called Neural-fuzzy systems combining the techniques of fuzzy modelling and neural networks. Neural-fuzzy models combine the advantages of fuzzy logic and neural networks, namely adaptability, quick convergence and high accuracy (Shie-Jue, Chen-Sen, 2003).

3. Proposed Artificial neural network model

The aim of the research is the use of artificial neural network methods in designing an order cycle of an enterprise. This paper deals with developing an ANN model which can be used to optimize inventory level and thus improve inventory management and order system of an enterprise. The variables of current demand, demand in the next 3 months, demand in 3 months following after the 3-month order cycle (3-month delay), current inventory level, purchase prices and transport costs are used as input parameters. Output data is the ordered quantity.

All input, output and sample data were provided by an existing company, a wholesale dealer with connecting materials. Being part of a supply chain, the company buys from an Asian supplier and has to allow for a replenishment lead time of up to 60 days from the date of order. The data represents the information about the highest-turnover type of goods on the company's assortment, as monitored from January 2009 to December 2014.

This study develops the model of neural network to determine the optimum amount of ordered goods to optimize the current inventory amount. The selection of input and output parameters is crucial for the model construction. The input variables for this model are the 6 most significant factors affecting decisions on ordered amounts. These are the current demand (monthly), demand in the next 3 months, demand in the following 3 months, current warehouse value, purchase price per unit and transport costs per unit. The output parameter of the model is optimal amount of purchased goods. Inputs and outputs are presented in Figure 1.

The neural network model has been constructed using the MathWorks MATLAB programme. The following steps need to be taken when constructing the model of neural network: collection of input, output and sample dataset, designing, training and validation of neural network.

Before using collected dataset with neural network, data must be processed into input-output patterns. Each pattern is formed with an input vector and the corresponding target vector . Input and

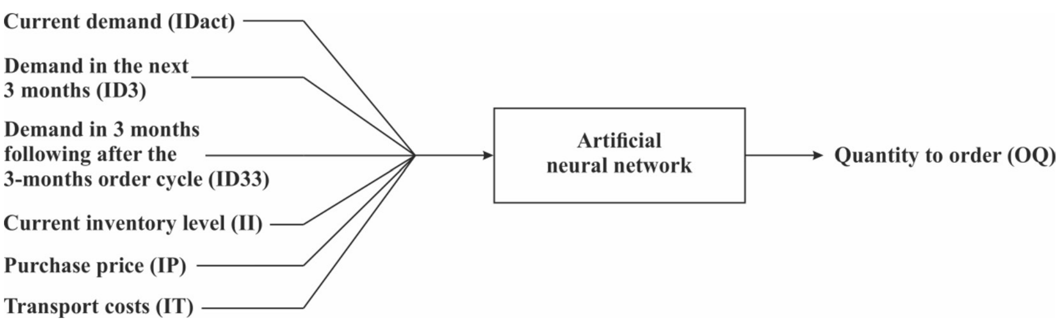

Figure 1. Diagram of the inputs and output of constructed neural network. Source: Author's own study.

Table 1. Example of standardized input-output dataset.

IDact	0.44	0.41	0.67	0.67	0.66	0.65	0.32
ID3	0.27	0.09	0.45	0.50	0.89	0.31	0.48
ID33	0.13	0.65	0.06	0.61	0.61	0.72	0.64
II	0.15	0.01	0.01	0.08	0.10	0.09	0.21
IP	0.72	0.30	0.41	0.59	0.43	0.63	0.60
IT	0.24	0.75	0.43	0.63	0.24	0.64	0.62
OQ	0.043	0.171	0.336	0.426	0.674	0.997	0.342

Source: Author's own study.

output data must be transformed into standardized form within the range of 0 to 1 in order to achieve consistent result while using ANN.

The standardization is done using the following equation:

$$X_i = \frac{x_i - \min(x_i)}{\max(x_i) - \min(x_i)}, \quad (1)$$

where is the i^{th} element of the input or target vector and X_i is corresponding standardized value within 0 and 1. An example of standardised input-output vectors is shown in Table 1.

A total of 31 input-output dataset pairs were collected. This dataset was divided randomly into two categories – training dataset which consists of 77% of the data and test dataset with 23% of the data. There are 24 training patterns, which are used further to model the artificial neural network. After completion of the network training the model is tested with 6 data samples and the network performance is evaluated. The sample of input and output dataset is shown in Table 1.

3.1 Neural Network Architecture

MathWorks MATLAB Neural Network Toolbox was used for construction of the inventory management model which provides functions and apps for modeling complex nonlinear systems that are not easily modeled with a closed form equation. With neural network toolbox it is possible to design, train, visualize and simulate neural networks; it can be used for applications such as data fitting, pattern recognition, clustering, time-series prediction, and dynamic system modelling and control.

A feed-forward backpropagation network model with one hidden layer and output layer is used, while the number of hidden neurons can be defined. As training function was used both TRAINGDX and TRAINSCG, adaptation learning function was used LEARNGDM, also TANSIG transfer function is used. The maximum number of training epochs is set to be 1 000 and the maximum number of validation checks is set to 1 000. The architecture of proposed ANN model is shown in Figure 2.

The neural network training is performed using 24 data samples containing both input and output data. The coefficient of determination value (R^2) for training phase is calculated to evaluate the performance of network during the training. Values of the R^2 indicator are between 0 and 1, the objective being to determine the accuracy of the predicted data. Therefore the closer the R^2 coefficient is to 1, the more accurate the neural network can be considered.

After reaching the best possible R^2 coefficient value the testing of newly emerged trained neural network is performed. The sample of 7 data vectors containing both input and output data is used for testing; however, for the neural network only the input vector is used. The neural network testing output is later compared to the real output value

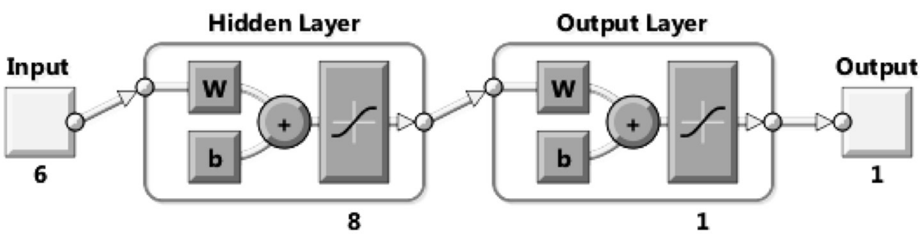

Figure 2. ANN architecture of proposed model. Source: Author's own study.

– *i.e.* with amount ordered in reality. The testing performance is evaluated by an error measure – Mean squared error (MSE). MSE is the average squared difference between outputs and targets. Lower values are better, zero means no error.

4. Results and Discussion

To evaluate a suitable artificial neural network for inventory level optimization and order cycle management. To find the best constructed artificial neural network with optimal architecture, 16 neural networks with the TRAINGDX or TRAINSCG learning function and with the TANSIG or LOGSIG transfer function were constructed, trained and tested. The number of neurons in hidden layer was variable too. The evaluation of optimal neural network was governed by the MSE value. Neural networks with lower MSE value and at the same time with R^2 value closer to 1 were considered more suitable.

The Table 2 shows R^2 and MSE values of the constructed neural network models. It shows the results of network training and testing with the TANSIG and LOGSIG transfer function and with TRAINGDX and TRAINSCG training functions for the respective values of hidden neuron numbers used for ANN. The overview indicates that neural networks using the TRAINGDX training function and the TANSIG transfer function generally performed better; with higher number of neurons the network performance tends to decrease. The lowest MSE values (0.029) and at the same time the highest R^2 values (0.99) are demonstrated by

Table 2. R^2 and MSE values of NN training and testing.

	TRAINGDX				**TRAINSCG**			
	TANSIG							
Neurons	8	10	12	15	8	10	12	15
R2	0.990	0.920	0.970	0.910	0.980	0.950	0.920	0.950
MSE	0.023	0.030	0.029	0.075	0.050	0.040	0.032	0.035
	LOGSIG							
R2	0.900	0.960	0.940	0.900	0.840	0.970	0.990	0.890
MSE	0.033	0.030	0.044	0.036	0.053	0.032	0.034	0.096

Source: Author's own study.

Table 3. Summary of optimal artificial neural network model.

Input data	6 – Actual month demand – Demand in next 3 months – Demand in 3 months following next 3 months – Actual stock level – Unit product costs – Unit transport costs
Output data	1 – Quantity
Network type	Feed-forward backpropagation
Training function	TRAINGDX
Adaptation learning function	LEARNGDM
Performance fuction	MSE
Number of hidden layers	1
Neurons in hidden layers	8
Transfer function	TANSIG

Training Parameters	
Maximum number of training epochs (iterations)	1,000
Maximum training time	Infinite
Maximum performance value	0
Minimum gradient magnitude	0.00001
Learning rate	0.01

Source: Author's own study.

the neural network with 8 hidden neurons; on the contrary the largest error (0.075) and the lowest R^2 value (0.91) is demonstrated by the neural network with 15 hidden neurons.

The absolutely best performance was shown by the neural network with 8 hidden neurons, TRAINGDX training function and TANSIG transfer function. Therefore, the neural network with the 6-8-1 architecture has been chosen as the optimal model for subsequent prediction and for designing the ordering system of a company.

Table 3 presents a summary of the proposed network architecture, consisting of 6 input neuron (inputs), 8 neurons in hidden layer and one output neuron (target). The R^2 and MSE indicators were used to find the optimal network architecture; these indicators were used for evaluation of each neural network.

5. Conclusion

The article investigates the options of using artificial neural networks and their applications in a company ordering system. Within the research a model of artificial neural network was developed to optimize the order amount as a function of current demand, demand in the next 3 months, demand in 3 months following after the 3-month order cycle (3-month delay), current warehouse values, purchase price and transport costs.

The architecture with feed-forward back propagation learning algorithm, TRAINGDX training function and TANSIG transfer function and 6-8-1 architecture was assessed as the most suitable neural network. A performance of neural network model was evaluated by Coefficient of Determination (R^2) and Mean Squared Error.

The constructed model of artificial neural network can be used for further order cycle optimization. The future order amount can be planned based on predicated demand and thus the inventory management can be improved as a part of supply chain management. The article presents artificial neural networks as very useful and bringing many opportunities for further research.

Acknowledgment

This paper was supported by grant FP-S-15-2787 "*Effective Use of ICT and Quantitative Methods for Business Processes Optimization*" from the Internal Grant Agency at Brno University of Technology.

References

Aburto, L., Weber, R. (2007). Improved supply chain management based on hybrid demand forecasts. *Applied Soft Computing*, (7)1, pp. 136–144.

Aggarwal, A., Park, J. K., Krarup, J. (1993). Improved Algorithms for Economic Lot Size Problems: An 0 (mn)-Algorithm for Structured Problems. *Operations Research*, 41(3), pp. 155–180.

Dostál, P. (2008). *Pokročilé metody analýz a modelování v podnikatelství a veřejné správě*. Brno: Akademické nakladatelství CERM. 342pp.

Drexl, A., Kimms, A., Seeanner, F. (1997). Lot sizing and scheduling — Survey and extensions. *European Journal of Operational Research*, 99(2), pp. 143–154.

Elmaghraby, S. (1978). The Economic Lot Scheduling Problem (ELSP): Review and Extensions. *Management Science,* 24(6), pp. 587–598.

Gaafar, L., Choueiki, M. H. (2000). A neural network model for solving the lot-sizing problem. *Omega,* 28(2), pp. 175–184.

Gammisch, M., Balina, S. (2015). Support of Risk Management through Careful Selection of Anti-corruption Measures–a Critical Evaluation of Compliance Management Activities. *Trends Economics and Management*, 9(22), pp. 9–18.

Gardner, M. W., Dorling S. R. (1998) Artificial neural networks (the multilayer perceptron) – a review of applications in the atmospheric sciences. *Atmospheric environment,* (32)14, pp. 2627–2636.

Goyal, S. K., Giri, B. C. (2001). Recent trends in modeling of deteriorating inventory. *European Journal of Operational Research,* 134(1), pp. 1–16.

Hachicha, W. (2011). A simulation metamodelling based neural networks for lot-sizing problem in MTO sector. *International Journal of Simulation Modelling,* 10(4), pp. 191–203.

Hamzaçebi, C. (2008). Improving artificial neural networks' performance in seasonal time series forecasting. *Information Sciences,* (178)23, pp. 4550–4559.

Harris, F. W. (1913). How Many Parts to Make at Once. In: *Factory, The Magazine of Management*, 10(2), pp. 135–152.

He, W. (2013). An inventory controlled supply chain model based on improved BP neural network. *Discrete Dynamics in Nature and Society*. 2013(1), pp. 1–7.

Ioana, A., Mirea, V., Bălescu C. (2010). Economic processes study through Fuzzy Logic. *Journal of Economic*

Computation And Economic Cybernetics Studies And Research, 44(2), pp. 129–137.

McNelis, P. D. (2003). Nonlinear phillips curves in the Euro area and USA? Evidence from linear and neural network models. *Computational Intelligence for Financial Engineering,* 2003(1), pp. 145–149.

Megala, N., Jawahar, N. (2006). Genetic algorithm and Hopfield neural network for a dynamic lot sizing problem. *The International Journal of Advanced Manufacturing Technology,* 27(11–12), pp. 1178–1191.

Novotná, V. (2012). The impact of the inflation and unemployment values from the previous period on the Phillips curve. *7th International Scientific Conference Business and Management,* 2012(1), pp. 147–158.

Novotná, V. (2014). Feedback Influence on the Behavior of Financial System. *Economic Computation and Economic Cybernetics Studies and Research,* 2014(1), pp. 217–231.

Paul, S. K., Azaeem, A. (2011). An artificial neural network model for optimization of finished goods inventory. *International Journal of Industrial Engineering Computations*, (2)2, pp. 431–438.

Rogers, J. (1958). A Computational Approach to the Economic Lot Scheduling Problem. *Management Science,* 4(3), pp. 264–291.

Rudiene, E. (2014). Lithuanian Retail Internationalization: Features and Prospects. *Trends Economics and Management*, *8*(20), pp. 58–67.

Shie-Jue, L., Chen-Sen, O. (2003). A neuro-fuzzy system modeling with self-constructing rule generation and hybrid SVD-based learning. *IEEE Transactions on Fuzzy Systems,* 11(3), pp. 341–353.

Wagner, H. M., Whitin, T. M. (1958). Dynamic Version of the Economic Lot Size Model. *Management Science*, 5(1), pp. 89–96.

Zhang, T. (2012). A Monte Carlo Analysis for Stochastic Distance Function Frontier. *Inzinerine Ekonomika-Engineering Economics,* 23(3), pp. 250–255.

Zipkin, P. H. (1991). Computing Optimal Lot Sizes in the Economic Lot Scheduling Problem. *Operations Research,* 39(1), pp. 56–63.

Received: 18. 1. 2016
Reviewed: 2. 2. 2016
Accepted: 20. 5. 2016

Ing. Tereza Šustrová
Brno University of Technology
Faculty of Business and Management
Department of Informatics
Kolejní 2906/4, 612 00 Brno
Czech Republic
Tel.: +420 54114 3709
E-mail: sustrova@fbm.vutbr.cz