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A HYBRID DECISION SUPPORT SYSTEM FOR IRON ORE SUPPLY

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Preliminary Note – Prethodno priopćenje

Many European metallurgical companies are forced to import iron ore from remote destinations. For these companies it is necessary to determine the amount of iron ore that will have to be ordered and to create such a delivery schedule so that the continuous operation of blast-furnace plant is not disrupted and there is no exceedingly large stock of this raw material. The objective of this article is to design the decision support system for iron ore supply which would efficiently reduce uncertainty and risk of that decision-making. The article proposes a hybrid intelligent system which represents a combination of different artificial intelligence methods with dynamic simulation technique for that purpose.

Key words: iron ore supply, hybrid decision support system, neural network, simulation, fuzzy sets

Hibridni sustav za podršku odlučivanja opskrbe željeznom rudom. Mnoge europske metalurške kompanije su prisiljene na uvoz željezne rudače iz udaljenih destinacija. Za ove tvrtke potrebno je odrediti količinu željezne rude koje će morati biti naručena i stvoriti takav raspored isporuke, tako da je kontinuirani rad visokih peći ne bude poremećen i da ne se ne stvaraju pretjerano velike zalihe te sirovine. Cilj ovog članka je da se dizajnira sustav za podršku kod odlučivanja za opskrbu željezne rude kojim bi se efikasno smanjila nesigurnost i rizik isporuke iste. Za tu svrhu u članku se predlaže hibridni inteligentni sustav koji predstavlja kombinaciju različitih metoda umjetne inteligencije i dinamičke simulacijske tehnike.

Ključne riječi: opskrba željeznom rudačom, hibridni sustav za podršku odlučivanja, neuronske mreže, simulacija, neizraziti skupovi

INTRODUCTION

Iron ore belongs to the strategic raw materials of metallurgical companies with full metallurgical cycle, including pig iron production. More than 80 % of world iron ore production nowadays comes from China, Brazil, Australia, and India [1]. Many European metallurgical companies are forced to import iron ore from remote destinations using sea transport and railway service. That is why the basic logistics decisions play key role here. It is necessary to determine the amount of iron ore that will have to be ordered and to do it well in advance. It is also necessary to create such a delivery schedule so that the continuous operation of blast-furnace plant is not disrupted and, at the same time, there is no exceedingly large stock of this raw material (i.e. inventory costs).

Iron ore supply is influenced by a number of stochastic effects which make the aforementioned logistics decisions significantly more difficult. The most important of these effects is the fluctuation in the demand for iron ore caused by variability of demand for metallurgical commodities (and the increasing recent world economic crisis) and by variability of delivery time caused, for example, by weather-related problems.

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The objective of this article is to design the decision support system for iron ore supply which would efficiently reduce uncertainty and risk of logistics decision-making.

EXPERIMENTAL WORK

Iron ore supply process has been assessed in a metallurgical company situated in Poland which buys iron ore from a supplier from Ukraine. The iron ore is transported by train. The basic starting point for stipulation of the delivery schedule is a quality forecast of demand for iron ore, i.e. proposal of a suitable forecasting model. Demand for iron ore in a period of 44 months was used to serve this purpose. Using the time series analysis, seasonal and trend component wasn't identified. With regards to the fact, suitable time series models had been chosen for demand forecasting.

Unfortunately, none of the classical models guaranteed a forecast with acceptable error rate (the required deviation from reality being 10%). The application of models, resulting from time series of iron ore demand only, was connected with the following problems:

1. Time series was disrupted by the world crisis impacts which resulted in significant decrease of demand for iron ore in the monitored period of time.
2. Time series did not affect the cycle component, the period of which is 5.9 years in metallurgical industry [2].

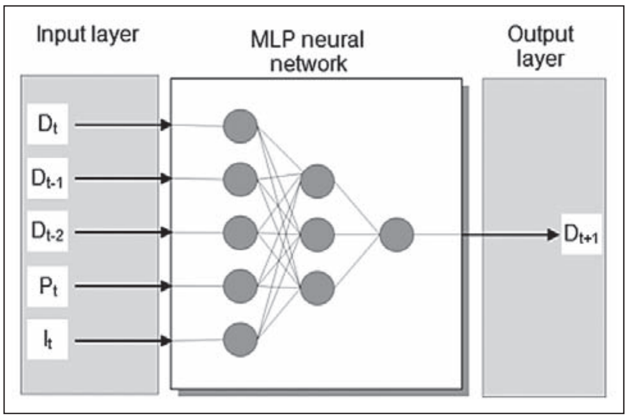

Figure 1 Artificial neural network forecasting model

That is why such models were searched as to make it possible to include not only the historical data concerning demand progress but also other factors which have an essential impact on prediction quality. Models using artificial neural network for forecasting comply with the above mentioned requirements. These models can be exposed to large amounts of data and discover patterns and relationships within them [3]. A multilayer perceptron (MLP) neural network model described in Figure 1 was designed.

The input and output layer consists of the following parameters:

D_t, D_{t-1}, D_{t-2} – historical data regarding demand for iron ore shifted by the equivalent time horizon (t).

P_t – difference between the planned and real production volume in previous periods (t).

I_t – CRU Steel Price Index in previous periods.

D_{t+1} – demand forecast of iron ore for the next month (t).

The variable P_t representing the difference between planned and real production takes into account a change of iron ore stock volume. If the real production is higher than the planned one the stock decreases and conversely. CRU Steel Price Index I_t takes into account the market development (CRU is a leading independent supplier of steel market information). Model is designed in such a way that the output is represented by the demand forecast of iron ore for the next month D_{t+1} (t).

Levenberg-Maguardt algorithm was used for learning the network. The network structure was learned, tested and selected up to the moment when error rate in the level of 10 % was achieved for the testing set. The model was verified using data of real demand for iron ore in the previous 20 months of the monitored period of time. It is obvious from Figure 2 that the designed model generates sufficiently exact forecast even for periods of significant decrease of demand.

The model used for forecasting iron ore demand was unnecessary static. The decision-making process concerning the creation of delivery schedule, i.e. the breakdown of the anticipated monthly demands for the individual deliveries from the point of view of volume and time is, however, of dynamic nature. A suitable dynamic model which would be able to cover the essential stochastic effects influencing the process of iron ore supply was searched for.

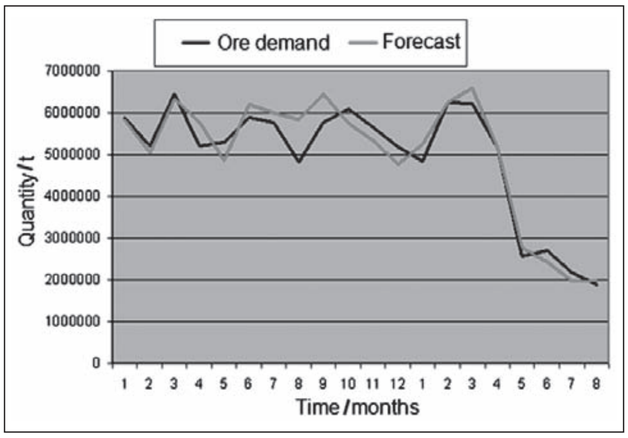

Figure 2 Verification of the designed forecasting model

The classic models in this area include fixed order-quantity system (continuous system) or fixed order-period system (periodic system) [4]. However, these models are encumbered by many simplifying conditions which make it impossible to cover all the important aspects of a real process dealing with iron ore demand, which is why they do not provide sufficient information for efficient decision-making. Thus the attention was shifted from analytical models to simulation techniques. Computer simulation is a method which uses computer model of company process to conduct experiments with the aim of achieving model parameters that are later applied back on the examined process [5]. With regard to the character of the iron ore supply process a dynamic stochastic simulation was used where time plays the key role [6].

Using methodology designed for dynamic simulation of metallurgical processes [7], a model of iron ore supply from Ukraine to a metallurgical company located in Poland has been constructed. The model includes a process of supply completion, their transport, unloading and storage in a buffer warehouse. The scheme of the model created in the environment of Dosimis 3® simulation software is illustrated in Figure 3.

The model is used to analyse the impact of volume and number of supplies on delivery time and the level of stock of iron ore within a company. The acquired outcomes can be used to determine such a delivery schedule that will provide the desired level of stock of iron ore in the company buffer warehouse.

Weather-related problems represent one of the most important aspects influencing iron ore supplies. The analysis concerning iron ore supply identified problems with delayed deliveries and maintenance of sufficient buffer stock in winter months. These problems are caused by trains bringing in frozen raw material, which makes it necessary to thaw the carriages during the un-

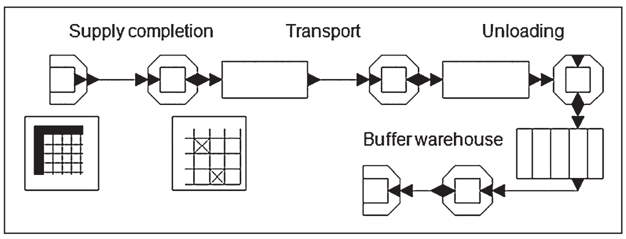

Figure 3 Dynamic model of iron ore supply

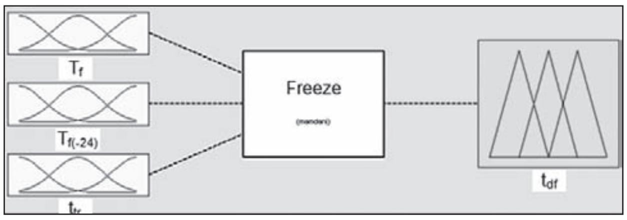

Figure 4 Structure of fuzzy model for thawing of frozen train carriages

loading process. This operation can take tens of hours when the temperatures are very low.

In order to be able to take into account the time needed for the necessary thawing of train carriages, a fuzzy model was designed. Fuzzy sets and expert knowledge of company specialists were used to create this model. The model structure is clear from Figure 4.

The model input and output variables are:

T_f – temperature on the day of train arrival in the company (°C).

$T_{f(-24)}$ – average temperature from the previous day (°C).

t_{tr} – train transport time to company (hours).

t_{df} – thawing time of train (hours).

Each variable was assigned an appropriate range of values which have been divided into three categories by means of trapezoidal membership functions. Thawing time of trains t_{df} (hours) is the outcome variable of the fuzzy model.

The expert knowledge of the company specialists helped to create a knowledge base which makes it possible to determine the thawing time in dependence on the values of the input variables of the model using „if and then“ type of rules.

RESULTS AND DISCUSSION

Experimental work proves that efficient decision support system for iron ore supply must integrate the outcomes of several models, utilising various approaches and techniques. A hybrid intelligent system which represents a combination of different artificial intelligence methods with dynamic simulation technique and conventional systems (such as database systems) can meet this objective.

The concept of such a system is illustrated in Figure 5. Its most important sub-systems are the sub-system forecasting the demand for iron ore (sub-system A) and the sub-system used for modelling and simulation of iron ore delivery time (sub-system B).

The essence of the system is to determine the iron ore demand by means of forecasting model based on artificial neural network. This forecast is used as input information for a simulation model which enables us to find a suitable delivery schedule of iron ore into a company. It is convenient to make provision for the case of delayed deliveries caused by frozen train carriages in winter months by revising the unloading time in the simulation model. Fuzzy model determining thawing time of carriages can be used for that purpose.

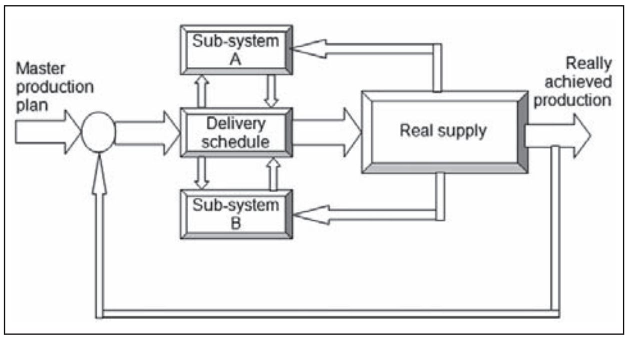

Figure 5 Concept of hybrid decision support system for iron ore supply

CONCLUSION

The concept of the designed hybrid intelligent system makes it possible to utilise the advantages and to overcome the limitations of individual artificial intelligence and conventional techniques. Mutual exchange of information from forecasting model, delivery time model, model of thawing trains, and the knowledge of current level of stock of iron ore are therefore sufficient for efficient logistics decision-making in the area of iron ore supply.

In the end, differences of iron ore supply processes in various European metallurgical companies must be pointed out, especially as for their technological and supply process parameters. Therefore sub-systems included in the hybrid intelligent system concept will have to be adjusted to specific conditions of each company.

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Note: The responsible translator for English language is Petr Jaroš (English Language Tutor at the College of Tourism and Foreign Trade, Goodwill - VOŠ, Frýdek-Místek, the Czech Republic). Revised by John Vlcek (Literacy Tutor at West Suffolk College, Bury St Edmunds, England)