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Telematics system architecture to manage the internal transport

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ABSTRACT
The purpose of the research is to provide a telematics system architecture. The technologies used in computer science belong to the most important instruments also affecting transport management in an enterprise. They may assist the utility of the system, its accessibility, the level of integration and substantially influence the performance of a company. The use of telematics tools will make it possible to optimize the supply chain within the company. This optimization applies to sales forecasting, which affects the material demand, production, etc. A mathematical model has been developed, which is based on the fusion of fuzzy classifiers with the theory of probability and the theory of mathematical evidence. The data affecting sales include, amongst other things: delivery lead time, sales records, customer satisfaction, delivery compliance rate, delivery speed ratio, supply excellence ratio, lead times between order taking and delivery, etc. The study has proven that soft calculation methods based on fuzzy sets and artificial neural networks are appropriate for the tasks of the logistics chain control, and the support of telematics tools will improve the management of an enterprise.

KEYWORDS: telematics system architecture

1. Introduction

The turn of the millennium is a time of intensive development of modern information and communication technologies in the developed countries of the world. Personal computers, computer networks and the Internet have become the symbols of this development. They have increasingly been used in almost all areas of social and economic life. As a result of their mass application, a new type of society is being developed, called the information society, where the information becomes a fundamental public good.

The number of enterprises engaged in forwarding activities is increasing each year. These enterprises are looking for methods to improve the quality of management and raise the operational efficiency. They decide on the implementation of telematics system to assist the flow, selection and grouping of information, and as a consequence the fleet management becomes easier and more efficient. A strong emphasis in the case of such a decision is placed on the selection of software and its suppliers. The very implementation is marginalized, which, in practice, affects the appropriate and consistent functioning of the system as expected. The intelligent implementation and use of information systems is the way to gain competitive advantage.

Information technologies do not develop in a market vacuum, but in close connection with the market situation and they meet specific needs. Sometimes they are ahead of the awareness of the existence of the demand in potential customers.

The use of information and communication technologies has also led to nearly total automation of data processing and transmission processes, in which the role of the human is limited merely to the exercise of supervision. Therefore, these solutions facilitate work and the exchange of information with the client, reduce the duration of logistic processes and eliminate human errors.

Examples of more or less advanced telematics technologies in transport are technical means (hardware and software, protocols, etc.) for:

- remote measurements of the condition of transport objects using such technical devices as for example sensors, detectors,
- data transmission over large distances by satellite and land-based communications systems,
- electronic and wireless exchange of information between a moving vehicle and roadside devices,

- gathering multimedia data for example in databases and data warehouses to ensure effective access to them,
- fast data processing, often multimedia data (texts, images, voices),
- providing information to users in real time, i.e. in parallel with the implementation of transport operations.

The variety of telematics solutions in transport systems is extremely high. It is worth noting at this point that telematics systems:

- are technological innovation in transport,
- their core function is to improve transport systems in the field of remote gathering information about dynamic transport objects, its processing in real time, efficient storing and fast forwarding, often on small or large distances,
- more integrate the whole transport system for information, especially its basic components: infrastructure, vehicles and transport operations, thus enabling better management of the transport system or its individual components.

The transport infrastructure is the foundation of proper functioning of the economy. Its development should be shaped on the basis of modernity and efficiency, particularly given the significant cost of this development. The support to properly designed information systems significantly allows to alleviate or completely exclude the defects and problems that occur when running a transport enterprise. Therefore, the aim should be to develop integrated strategies for the promotion and implementation of modern transport solutions, which, when introduced, will contribute to improvement in the availability and quality of passenger and freight transport services, and reduce the impact on the environment.

The implementation of a telematics system is a very complex undertaking and constitutes the largest investment in an enterprise taking into consideration costs, complexity and time of implementation. This operation is not limited to the purchase of computers, wireless devices and the installation of the software.

The article presents the architecture (model) for the collection and processing of information in the internal transport of information, which forms the basis of business management.

The proposed original Fuzzy-ProgKM classifier uses a fusion of classifiers related to the probability, the theory of fuzzy sets and mathematical evidence theory. A telematics system in the form of sensors that measure inventory size sends the information to ERP system in real time. This information comes from a variety of sensors and it requires special mathematical methods to aggregate such data and make decisions. For this reason, a sequential approach proposed [2, 6, 7] for the task of forecasting is an essential part of the algorithm, since in addition to the current state of the earlier observations, the observation of previous measurements significantly contributes to an increase in the precision of the forecasts. The main inspiration for this model was to describe the creation of a method that, in contrast to statistical methods, will cope better with uncertain, imprecise data which we are witnessing mainly in stochastic processes. Undoubtedly, these kinds of data occur during inventory forecasting since their size is dependent on changes in demand on the market which are often difficult to estimate. In order to authenticate the results of the original model, its results of forecasting (convergence, error) were compared to Holt-Whinters forecasting algorithms, known from the literature [1,8].

2. Mathematical description of the task of inventory forecasting

Before describing the task of inventory forecasting a scheme of architecture for internal transport of information within a telematics system is shown in figure 1.

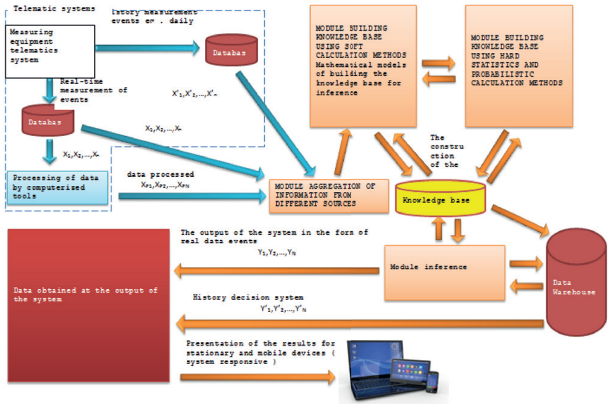

Fig. 1. Scheme of architecture for internal transport of information within a telematics system [own study]

The devices of the system gather information in real time on inventory stock, orders to warehouse, orders for production. From various chains of an enterprise the information is transported using TCP/IP protocols to the aggregation module of information coming from different sources. Then the information gets to the modules of information processing and decision making. These modules have the task to recognize the task of classification.

The task of sequence recognition based on the fusion of classifiers will be treated as a dynamic process. An object in k-th interval is in the Y_k state that belongs to the quantitative category $y_k \in R_+$. The state of the y_N object is not subject to direct measurement. It is the result of observation of the object's trend, and more specifically a trajectory of earlier measurements $Y_{k-1}, Y_{k-2}, \ldots, Y_{k-l}$. Let $x_k \in \mathbf{X}$ be a (d)-dimensional vector of variables (characteristics), which have been measured in the preceding intervals. These variables in the case of stocks are the delivery time, customer service ratio and other variables that can serve as a basis for determining the size of stocks. These variables are subject to fuzzing $\widetilde{T}_i$ [3.4] by fuzzy sets, where:

$$\widetilde{T}_i = \left\{ \widetilde{T}_1, \widetilde{T}_2, \widetilde{T}_3, \ldots, \widetilde{T}_d \right\} \tag{1}$$

In further considerations n will mean n-th fuzzy rule:

$$n = \{1, 2, \ldots, N\} \tag{2}$$

In the analysed case the current state of the object is dependent on previous states, i.e. used inventory control. Let $Y_{k-1}, Y_{k-2}, \ldots, Y_{k-l}$ be objective functions.

Combining the current observation of the object's characteristics with the previous state is a simplification. It is possible of course to analyse all object's states so far but this interpretation can be difficult to take into account.

Making a decision on the planned inventory levels at k+1 moment is dependent on the measurement of the characteristics describing it and the knowledge about the relationships between successively occurring measurements of stocks (trends) and features describing the size of the stocks. This knowledge is stored in a learning set, which consists of a set of learning sequences:

$$S = \{S_1, S_2, S_3, \ldots, S_L\}. \tag{3}$$

A single learning sequence can be written as follows:

$$S_k = (x_1, x_2, \ldots, x_d). \tag{4}$$

S_k- means an observation of specific k object. In the case of inventory planning S_k is the measurement of characteristics that describe the volume of stocks, for example delivery time, customer service ratio. Sequential recognition task will mean the fact that the decision-making algorithm in the k-th interval to decide on the forecast of stocks for the next period will use the information in the form of previous stocks volumes, delivery times and customer service ratio.

The error on a learning set can be defined:

$$error_S = \frac{1}{|D|}\sum_{x \in S} \delta\left[Y^*{}_{k+1} \notin Y_{k+1} \pm q\right], \tag{5}$$

Where $\delta\left[Y^*{}_{k+1} \notin Y_{k+1} \pm q\right]$ takes the value 1 if the condition is fulfilled and 0 if it is not fulfilled. Value q is the value described by an equation (6).

$$q = \sqrt{\frac{1}{4}\sum_{i=k-4}^{k}\left(Y_i - \frac{1}{4}\sum_{i=k-4}^{k} Y_i\right)^2} \tag{6}$$

Let us assume that we have d of decisive classes. Then the differentiability function will be function $F{:}D \rightarrow R^d$. Let $F=(f_1,\ldots,f_d)^T$. Object x is allocated to the class with the highest support ratio, i.e. if:

$$M = \max_i \{f_i(x)\} \tag{7}$$

In sequential recognition we assume certain weights $p_1,\ldots,p_n$. These weights can be interpreted as distributions of probability. $\langle x_1, Y_1\rangle, \ldots, \langle x_n, Y_n\rangle$. While learning we select examples from the set S in accordance with the distribution of basic probability P. As a fuzzy observation of features was adopted at the beginning, therefore for such a case, an appropriate weighted error shall be adopted:

$$error_{k+1} = \sum_{j=1}^{n} p_j^{(k+1)} \mu\left(\widetilde{T}_i\right) \delta\left[Y^*{}_{k+1} \notin Y_{k+1} \pm q\right], \tag{8}$$

The weight ω_{k+1} is calculated according to the equation:

$$\omega_{k+1} = \log\sqrt{\left(\frac{1 - error_{k+1}}{error_{k+1}}\right)} \tag{9}$$

$$p_{j^*}^{(k)} = \begin{cases} p_j^{(k)} \exp\left(-\varpi_k \cdot Bel\left(\mu\left(\widetilde{T}_i\right)\right)\right) & dla \quad Y^*{}_{k+1} \in Y_{k+1} \pm q \\ p_j^{(k)} \exp\left(\varpi_k \cdot Bel\left(\mu\left(\widetilde{T}_i\right)\right)\right) & dla \quad Y^*{}_{k+1} \notin Y_{k+1} \pm q \end{cases} \tag{10}$$

where $Bel\left(\mu\left(\widetilde{T}_i\right)\right)$ is a function of belief according to Dempster-Shafer theory regarding belonging to the fuzzy set $\widetilde{T}_i$.

In order to satisfy the condition $\sum_{j=1}^{n} p_j^{(k)} = 1$, a simple standardization shall be made:

$$r_k = \sum_{i=1}^{n} p_{i^*}^{(k)} \tag{11}$$

where:

$$p^{(k+1)} = \frac{p_{j^*}^{(k)}}{r_k} \tag{12}$$

In general, the algorithm can be written as:

$$\psi_{k+1}\left(p^{(k)}\widetilde{T}_k, p^{(k-1)}\widetilde{T}_{k-1}x_{k-1}, p^{(k-1)}\widetilde{T}_{k-2}, S\right) = Y^*{}_{k+1} \tag{13}$$

It is a combined classifier using the fusion of fuzzy Bayesian classifier with a fuzzy observation of previous stocks values.

The algorithm is written in a general form and its arguments are dependent on the complexity of the parameters used in the assessment of stocks. The sequential recognition process can is presented in diagram 1.

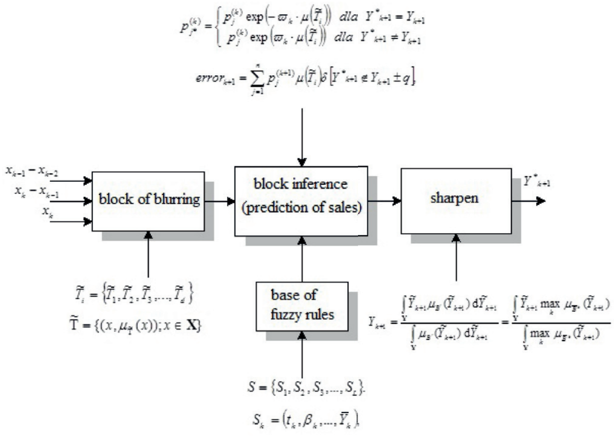

Fig. 2. Fuzzy illative system [own study]

In the model presented in fig. 2 the current use of stocks on the input is defuzzified Y_k once the differences of vectors describing the size of the consumption of inventory between k and k-1 interval as well as the differences between k-1 and k-2 intervals. The values are subject to the process of fuzzification. Next, based on all available knowledge accumulated in the learning set in an interference block, a fuzzy mapping of fuzzy quantities is planned $\tilde{T}_k$ into a fuzzy set. In the process of defuzzification, the fuzzy set Y_{k+1} is transformed into crisp value Y_{k+1}.

3. Conclusion

The article describes the architecture of information transport system within an enterprise. This information is used in the process of recognition. A telematics system collects information from a variety of sources. This information includes the availability of the whole transport infrastructure inside the company, inventory, history of measurements, availability of employees, information on material demand MRP and ERP forecasting. All information is collected from recorders, measuring probes, motion sensors, RFID system (automatic identification). This whole trajectory of measurements allows for the development of a forecasting system to keep the inventory at an optimum level. Due to the high complexity of the data it is necessary to create a hybrid model in the process of inference. This model combines the methods deriving from soft computing methods (fuzzy sets, artificial neural networks). It also includes hard methods, i.e. probability. The aggregation of knowledge in the knowledge database which is based on fuzzy rules gives the ability to describe the entire complex structure of data that are often incomplete, imprecise and incomplete.

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