Intelligent decision support for small business using expert systems and neural networks

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Abstract: *Previous research in intelligent decision support was mostly focused on large companies since it was very demanding regarding data, computer and human resources. This paper discusses the architecture of an intelligent system for small business taking into account specific characteristics of small enterprises that put some additional requests into such systems. Additionally, two intelligent systems for supporting decisions that entrepreneurs frequently deal with are developed and their results are described. An expert system for location decision support is created and a backpropagation neural network for sale prediction is modelled using a croatian small enterprise data. The results show that entrepreneurs can benefit from such systems and that the more detailed research is needed.*

Keywords: *expert systems, intelligent decision support, location decision, neural networks, sale prediction, small business*

1. INTRODUCTION

Today market-driven modern organizations need information systems that will be highly adaptable and able to minimize the risk [4]. Intelligent systems with data warehouse and data marts offer decision support that will be flexible enough to respond to such dynamic market behavior. Majority of previous research and applications on intelligent systems were focused on large companies. The reasons for not applying such systems in small companies were high demands in data, computer and human resources needed to develop such systems. However, new information and communication technology (ICT) brings evident changes into those requirements. It lowers the cost of hardware such that its price per performance ratio enables more companies to store lots of data and run demanding applications using personal computers. Information and data distribution through the Internet enables inexpensive access to databases and makes the market global even for small companies. New ICT also improves the availability of sophisticated expert knowledge through various intelligent software tools. The fact that business intelligence methods are being incorporated in DBMS systems through on-line analytical processing and data mining, makes possible that small companies benefit from such systems. The role of data warehouse and data marts in strategic decision making is increasing rapidly. Tanrikorur [14] emphasizes that DSS needs good planning from the start. Because of the specific characteristics of small businesses (existing information system mostly on transactional level, the lack of data warehouse, the lack of in-company ICT professionals who can contribute in system development, frequent usage of outsourcing, low budget etc.), it is necessary to adopt the architecture of intelligent decision support systems (IDSS) in order to fulfill the specific requirements of small businesses.

This paper discusses the architecture of an IDSS for small business, suggesting some modules and components that should be included in such system. The paper does not pretend to offer an integral IDSS solution for small enterprises, but discusses a conceptual framework for using technologies that reflect decision makers' way of reasoning. In addition to that, the design of an expert system and neural networks for some of the typical problems that entrepreneurs deal with is also given. Data was collected in a Croatian small company that employs 15 people, and produces and sells six groups of paint colors. An expert system for location decision support is designed, and a neural network system for sale prediction is created that can be included in the proposed intelligent DSS.

2. PREVIOUS RESEARCH RESULTS

According to [11], intelligence of a decision support system underestimates the following characteristics: (1) to be able to find relationships among data and to suggest interdependence models, (2) to be able to find relationships in the content of documents, (3) to be able to produce new knowledge on the basis of incorporated knowledge and to justify its decision, (4) to be able to learn the behavior rules and to suggest future behavior with the assumption of relatively little change in conditions. Regarding the above capabilities, DSS systems can be divided into: (a) document-driven, (b) data-driven, (c) model-driven, (d) communications-driven, and (d) web-based DSS. Developed systems vary from simple ones for relatively narrow domains, to very complex applications covering lots of business functions, processes, and events. The level of complexity in the system (i.e. software solutions) is connected to the complexity level of data, hardware and software organization (operational systems, databases, communication networks, as well as system adaptability) and the cost of the system. Due to the high cost of complete application packages and their implementation, separate modules are also available at the market, together with consultant services for the special types of problem that are being solved by a software solution. Available complex and integrated software packages cannot completely satisfy the need for solving complex business problems, since their solutions are not able to cover specific characteristics of all business situations and all managers' decision making styles. Moreover, software solutions frequently impose different approach or reasoning than decision makers use on different levels. Higher complexity of the system implies longer time needed to learn and use its capabilities. User-friendly graphical interface, as well as customer support is very important and time-consuming elements of all IDSS software solutions.

Classical approach to DSS architecture [3] includes five main components of a DSS: (1) system for data base management, (2) system for model base management, (3) system for document base management, (4) user interface, and (5) decision maker. Slightly different terminology is used by Power and Karpathi [10] who propose the following components: dialog management (which includes hardware and software needed to create user interface), database management, and model management. They define DSS architecture as the mechanism and structure for the integration of the dialogue, database and management components of DSS. Sprague and Carlson in [10] discussed four architectures for building an integrative DSS: the network, the bridge, the sandwich, and the tower. The dominant DSS architecture today is the network DSS, based on the client-server concept.

Resent research on data component of DSS architecture [14], [15] was mostly focused on data warehouse (DW) and data marts (DM) as data architectural options to interface with today's DSS. Tanrikorur emphasizes main differences among data warehouse and data marts describing data warehouse as a top-down approach covering multiple subject areas, while data marts represent bottom-up approach usually covering one subject area. Since DW is aimed to be applied on the corporate level, it requires more initial effort and cost, more project time invested, as well as higher level of expertise. DM requires less initial effort, lower cost, lower expertise level, and allow more migration. DW and DM can exist independently or collaborate with each other in a DSS. Since data marts are subject specific and smaller in scope, they produce faster results. Tanrikorur [14] suggests three different strategies to implement DSS: (1) top-down strategy – that starts from creating one large DW, and follows with creating smaller specific-purpose databases (DM) later, (2) bottom-up strategy – starts from creating DM for specific business areas and migrates to a common DW, and (3) hybrid approach –starts with creating departmental DM, and DW at the same time. The authors suggest that the latter approach, originally proposed by Gill and Rao in [14] is the most efficient, since it takes into consideration specific needs as well as their integration into a common DW, therefore enabling high scalability of the system. Vahidov and Fazlollahi [15] propose a framework for a pluralistic multi-agent decision support system (MADSS). Their pyramidal architecture of IDSS include information agents at the intelligence level, expert systems at the design level, confronting agents at the choice level, and a decision maker.

Regarding the methodology and models included in IDSS, previous research offers various methods that can be used in IDSS. On-line analytical processing (OLAP) and data mining are used as query tools to view and analyze data that resides in either a DW or DM [14]. Gregoriades and Karakostas [4] propose a simulation methodology based on the combination of business objects and system dynamics that assists organizations in predicting future behaviors. Hwang et al. [5] investigated the critical factors for adoption of data warehousing system in banking. Their results showed that among other features, the size of the bank also affects the adoption of data warehouse technology. Since the small size is one of the main characteristics of small companies, it stresses the need for investigating this relationship in more details. Other features of influence were the support from the top management, effect of champion, internal needs, and competitive pressure.

It can be concluded from previous research that the most common architecture proposed for IDSS is the network architecture, but its components are not adapted to small business needs. There are variety of methods and models proposed for IDSS systems, such as simulation models, statistical methods, expert systems, neural networks, and others incorporated in data mining, while the recent concepts on the data level are focused to data warehouse and data marts. Agent-based architecture is a new approach at the module level of IDSS.

3. ARCHITECTURE OF INTELLIGENT DECISION SUPPORT SYSTEM FOR SMALL BUSINESS

The architecture of an IDSS is mostly determined by: its goals, its tasks, the complexity of covered solutions, incorporated methodology, technologies that dominate at certain solutions and their combinations, the number of users, and the organization of decision making process (for details of IDSS categorization according to above criteria see [11]). When proposing the architecture of an IDSS for small business, it is necessary to take into account specific characteristics of small business. Due to its size, the budget of a small entreprise is usually lower comparing to a large company budget. Small business information systems are mostly developed on transactional levels, with very little managerial decision support. They usually contain only DBMS systems, without data marts or data warehouse. The process of developing the system is harder when there is a lack of in-company ICT professionals, which is the case in most small businesses (except in those where ICT is the main activity). Therefore such companies frequently use outsourcing for some expert services, which makes transfer and storage of knowledge harder to achieve. It is necessary to adopt the architecture of intelligent decision support systems (IDSS) in order to fulfill the specific requirements of small businesses. Small businesses are also very flexible in changing their activity. Regarding the above characteristics, the IDSS for small business needs to incorporate the following specific characteristics: low cost of implementation and maintenance, high scalability and adaptability, simplicity for usage (user-friendly GUI with the explanation of results), modularized, ready-to-use with short implementation time, minimal number of data transformation needed, low-risk, and effectiveness. Since managing expectations was the most challenging aspect of building such a system according to Sentry Market Research survey [14], before building any DSS it is necessary to define expectations of its users. The users are about to define criteria of successfulness of such system regarding to the company goals. For example, if the goal of a company is to achieve 20% growth of sale by the end of this year, then the IDSS needs to be structured in the way that it is oriented toward market and customers, which requires different models and data organization then in the case if the goal is to reduce the cost of labor.

The architecture of an IDSS for small business should be based on the generic IDSS architecture, with subsystems in the simpler, and more flexible form. Therefore, we suggest that it contains the following subsystems: (1) data and document management, (2) modeling management, (3) knowledge management, and (4) decision maker. It is presented grafically on Figure 1.

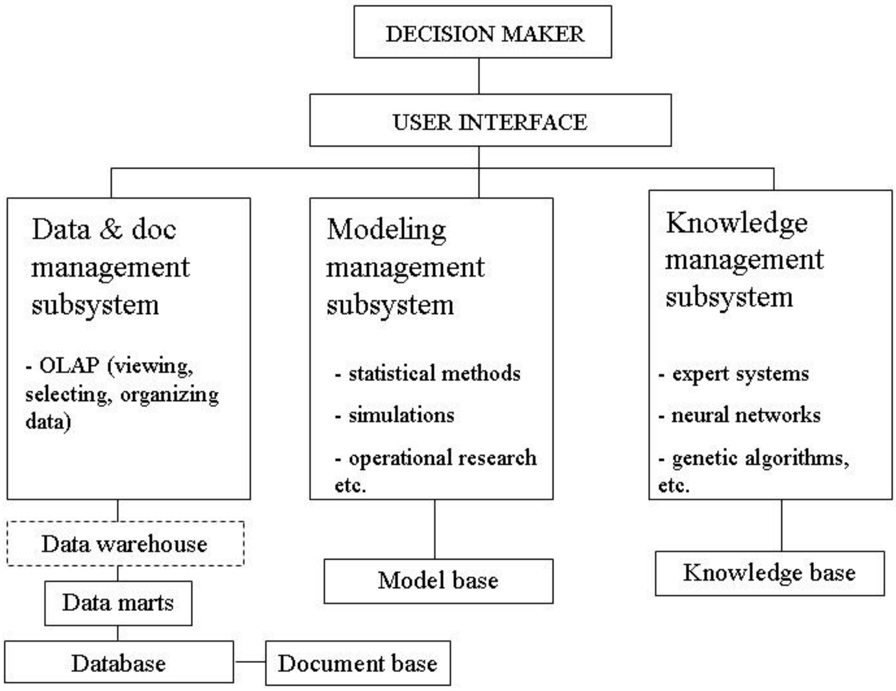

Figure 1. The architecture of an IDSS for small business

The first subsystem joins together the management of data and documents since the new technology enables communication and transformation among them (for example through xml). However, it should be built trough two important development levels: (a) starting level based on data marts – to be used when a small company starts to implement IDSS, and (b) growing level based on data warehouse – that will be filled during time, and have its full function when the small enterprise grows to a company or during the long life period of an entreprise. Due to its small scope, scalability, low cost and expertise level, data marts are chosen as the basis of this component. A small company can start with only one data mart and increase their number through time if needed. The bottom-up approach described in [14] is incoporated here, which assumes builing data marts for specific subjects first, and designing the structure of a data warehouse in the later phase of a company development. It is important to emphasize that design of data marts needs to take into account how it will be connected to the data warehouse later. The initial data flow starts from the ERP which constantly fills a DBMS with the data. Due to the selected goals and tasks of the IDSS, data marts are constructed and regularly updated from the DBMS with respect to the design of the data warehouse. It can be viewed, selected and organized using OLAP query tools. This subsystem can deal with some classes of structured problems, such as ABC analysis,

The second subsystem manages models with the purpose to select appropriate statistical, operational research or other models for typical classes of small business structured decisions, such as transportation problem, supply optimization, prognoses, etc. Trend analysis, ABC analysis, correlations, top-bottom analysis and other methods can be very usefull in these types of problems. The third, knowledge management subsystem of a small business IDSS has the purpose to cover unstructured decisions such as technology selection, location selection, investment decisions, predictions, etc. It contains expert systems, decision trees, neural networks, generic algorithms, support vector machines. Intelligent agents together with expert systems can be used here to select appropriate method or model. Since expert systems are able to explain its decision to the user, we strongly recommend them for do the communication with the decision maker, explaining the result by transforming sophisticated results of computational methods to the manager in easily understandable terminology. Both first and second components communicate with the user through the user interface, which should enable local access and remote through Internet.

Such architecture satisfies most of the criteria for small business IDSS defined previously: it is highly scalable since it starts with small elements such as data marts and builds a data warehouse eventually. Availability is satisfied due to the fact that OLAP servers are now available in most relational DBMS packages (for example: SQL server, Oracle), and therefore not very cost demanding. The usage of datamining techniques is possible on both starting (datamarts) and growing levels (datawarehouse). The problem of low expertize in small business for using advanced datamining techniques can be solved by expert systems and intelligent agents, that will incorporate the knowledge of how to choose the appropriate method and model in their knowledge base, and will do the choice of methodology instead of the decision maker. The criteria of simplicity and clearness will be satisfied by having an expert system to explain the results to the user.

Inductive and deductive reasoning in expert systems, as well as their orientation to the problem (i.e. goal) and the capability of using variable descriptors and values with a very intuitive character for a decision maker, make this methodology very suitable for small business. Expert system are able to incorporate very large number of simple rules in their knowledge base. With available experts for specific business problems, those rules can be defined well enough to produce the solution that will satisfy the decision maker. The insight into those rule will enable the decision makers in small business to discover the unexpected cause-effect relationships among variables, or make them to search for new predictors. Discovering new relationships will frequently change their goals. On the other hand, knowledge discovery in the large amount of business data will enable effective predictions of future variables and events. Neural networks, genetic algorithms, statistical methods and other methods can contribute much in such predictions. The combination of the above techonologies (for example using neural network output as an input to an expert system) has been investigated as an effective tool to provide a very realistic picture of business situations.

As an example of how to design models that will be incorporated into proposed IDSS architecture for small business, an expert system for small business location, and a neural network system for sale prediction are developed and described in further text.

4. EXPERT SYSTEM FOR SMALL BUSINESS LOCATION DECISION SUPPORT

Expert system for small business location decision support is created using the XpertRule shell. The investigated problem was the selection of location for the new production and sale building of a small business company mentioned previously. Although this type of problem does not occur very often in companies, the managers of the observed company plan to open new sale locations in the city and in other towns throughout the region. Since the problem will occur more than once, it was reasonable to build an expert system that will support the location decision. The knowledge aquisition was partially done by interwieving experts, while the other part of the knowledge was discovered by generating decision rules. According to the structure level, the variables in the decision tree were divided into hard-structured and soft-structured. The goal itself (the location decision) contains elements of soft structure. Soft structure of the goal is implied by the limitied ability of decision maker to anticipate the future of the system and the environment. For these reasons, the created systems should be taken as a preliminary, and its functional version will have to be upgraded with additional variables and revided goals.

The possible values of the outcome variable LOCATION were defined as: "pass", "rethink", and "no pass". One of the outcomes was defined as "rethink" indicating a certain lack of expert knowledge or uncertainty of decision maker in some situations, while recommending the decision maker to reconsider the decision in the context of other possible conditions. The goal (outcome) as well as the variables and their defined values are shown in Table 1.

Values	INFRA STRUCTURE	WAREHOUSE	COMPETITION	SIZE	ROADS	OUTCOME-LOCATION
	OK	EXCELLENT	NO_INFLU	EXTRA	GOOD	Pass
	SMALL INV	ACCEPT	WEAK	ACCEPT	ACCEPT	Rethink
	CONS_INV	BAD	HIGH	REJECT	BAD	No pass
	HUGE_INV					

Table 1. Outcome, variables and their values in the ES for location decision support

The structure of the task (project) is presented on the Figure 2.

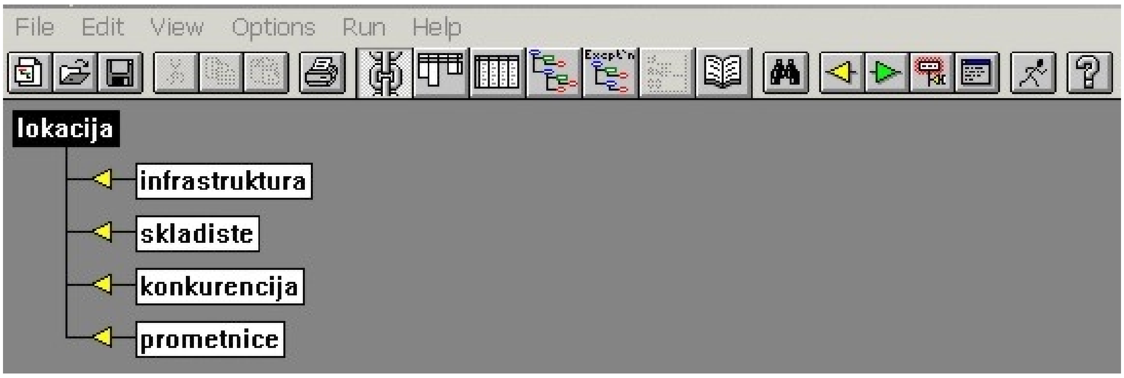

Figure 2. Structure of the task (project) in the ES for location decision support

Each of the above variables is furtherly analyzed as a subtask using the backward chaining. For example the variable COMPETITION has the following decision variables: strength of the competition (strong, not threatening, neglet it), the possibility of the cooperation (realized, possible, no possibility), and the distance of the competition (very near, near, far away). Figure 3. shows the variables forming the COMPETITION subtask and its values.

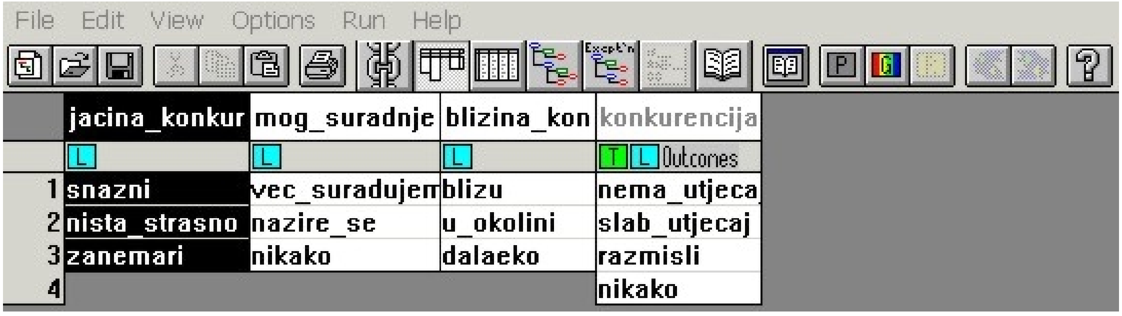

Figure 3. Structure of the backward chained task COMPETITION

Decision rules are entered directly through the decision trees. A part of the decision tree is shown on Figure 4. By entering the characteristics of influence variables it is possible to quickly reach the recommendation for the solution. While testing the system, four different locations were analyzed. The recommendation of the system for two of them was "no pass", one received a recommendation "rethink", while another one received the "pass" decision.

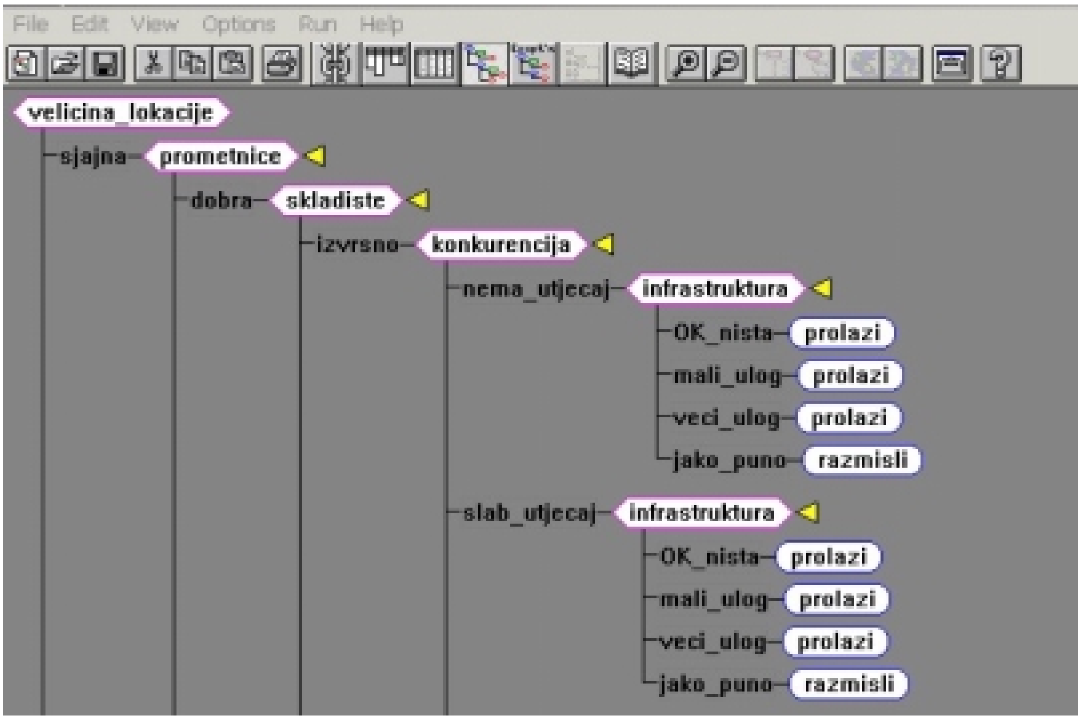

Figure 4. Part of the decision tree for the location decision support

In order to use the system in the wider contest – for location assessment of the retail companies or indirectly for the selection of business partners, the structure of the system should be upgraded and revised. Due to the fact that the new variables can be easily added into the knowledge base and modified, the adaptability of the system is very high. The system has also the capability to explain the way it generated the decision, and is easily transfered to the web interface. Although such expert system is financially more justified for large companies, a small entreprise can benefit from it if their location decision influences the sale significantly or sometimes is vital for the survival of the entreprise. There should not be expected that managers in small enterprises learn the methodology of expert systems. They need to communicate with the system through an understandable interface getting the results in easily understood forms. If they understand the essence of the technology behind the system, the results can be remarkably effective. By using expert system shells, decision makers will become aware the number of factors that influence their decisions, and will develop the ability to recognize cause-effect relations. Expert system can also help to clearly set the business goals, and in some situations to recognize the necessity of changing those goals and their priorities. For example, if a small enterprise faces the problem of whether to employ a knowledge engineer or a manager, ES can offer a support to that decision. Due to the specific characteristics of small business, it is suggested to use expert system shells [1].

5. NEURAL NETWORKS FOR SALE PREDICTION

5.1. DESCRIPTION OF NEURAL NETWORK ALGORITHM USED

The reasons why NNs often outperform classical statistical methods lie in their abilities to analyze incomplete, noisy data, to deal with problems that have no clear cut solution and to learn on historical data. Because of those advantages, they have shown success in predictions of financial data series that have high degree of volatility and fluctuations. Among the disadvantages of NNs, it is necessary to mention the lack of tests of statistical significance of the NN models and parameters estimated [12]. Despite the disadvantages, many research results show that neural networks can solve almost all problems more efficiently than traditional modeling and statistical methods. It is mathematically proven that three-layer neural networks having arbitrarily squashing transfer function are capable to approximate any nonlinear function [8].
Backpropagation is a general-purpose supervised NN algorithm [16]. In its classical form it involves error optimization using the deterministic gradient descent algorithm, and has has multi-layered feed-forward structure, shown in the Figure 5.

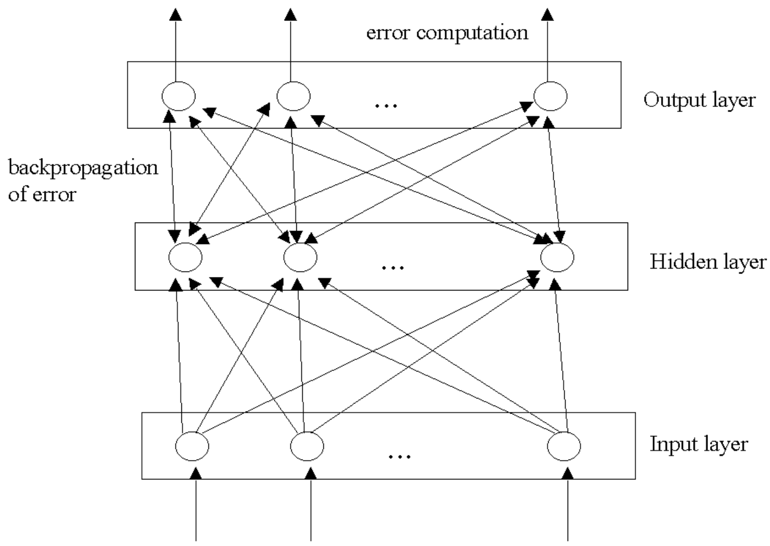

Figure 5. Architecture of the backpropagation neural network

When the input layer sends data to the first hidden layer, each hidden unit in the hidden layer receives weighted input from the input layer (initial weights are set randomly often ranging from –0.1 to 0.1) see details in [8]. Units in the hidden layer transfer those inputs according to a function, usually the sigmoid or hyperbolic-tangent function [16]. At the output layer, the network output is compared to the desired (real) output, and the global error E is determined as:

$$E = \frac{1}{2}\sum_{k}(d_k - x_k)^2 \ , \tag{1}$$

where d_k is a desired (real) output, while x_k is the output of the network, and k is the index for the component of the output, i.e. the number of output units. The objective of the Backpropagation learning process is to minimize the above global error by backpropagating it into the connections through the network backwards until the input layer. By modifying weights, each connection in the network is being corrected in order to achieve a smaller global error. The process of incrementing or decrementing the weights (i.e. the learning) is done by one of the learning rules, such as the Delta rule which is used in our experiments.

The backpropagation algorithm is chosen for our research because the previous research has proven it applicability to the problems with non-linear dependencies in data, financial time series and multiple regression models [8], and for the reason of its general purpose and availability in almost all NN software tools. When selecting the software for building our NN models, we took into account the criteria of availability and simplicity, in order to make it accessible to entrepreneurs as potential users. For these reasons we used the Backpack software.

5.2. NEURAL NETWORK MODEL FOR SALE PREDICTION

One of the critical problems in the observed small enterprise was to predict their sales in order to efficiently plan the inventory. Ordering more raw materials than needed for one week of production usually results with solvency problems, while ordering insufficient amount of raw materials produces inability to deliver the ordered goods. Therefore the prediction should be made on a weekly basis for company's six main product groups: (1) wood and metal paint colors – noted as SALE1 in NN models, (2) wall paint colors – SALE2, (3) nitro enamels – SALE3, as well as three sorts of car paint colors: one-component enamel mix – SALE4, two-component acrylic enamel mix – SALE5, and component base coat mix – SALE6. A neural network model was developed for each product group in order to predict the amount of sale of that group in the next week. The output variable was the continuous value of sale in the next week. While choosing the input variables, we assumed that the future sale is affected by previous sale and some exogenous variables. Previous sale is included in the models by using the amount of sale in the current week – SALE_CURRENT, the amount of sale in the previous week – SALE_PREVIOUS, and the amount of sale in the same week last year – SALE_LY. Additionally we assumed that the number of buyers in the observed time period also influence the sale - BUYERS, as well as the existence of promotion activities in the observed time period - PROMOTION, the existence of educational seminars - EDUCATION, and sale actions - ACTION. Historical data shows that the sale of all observed groups of products except wall paint colors is seasonal with higher sale during spring and summer. Therefore, we included the seasonal effect as a fuzzy variable - SEASON. In order to compute probabilities for the fuzzy variable, a membership function is defined such that the extreme points were the following: starting point was the fourth week of January; the top was in the period from the first week in March till the fourth week in October, while the ending point was at the last week of October. Computed probabilities in this fuzzy variable express the presence of a high-sale season. Table 2 shows descriptive statistics for exogenous input variables, while Table 3 shows the same statistics for the output variables in each of the six models.

Variable code	**Descriptive statistics**
BUYERS	mean: 195, stdev: 45.28
PROMOTION	yes: 27, no: 116
EDUCATION	yes: 2, no: 141

ACTIONS	yes: 14, no: 129
SEASON	mean: 0.57, stdev: 0.46

Table 2. Exogenous variables in all neural network models with their descriptive statistics

Variable code	Descriptive statistics					
	NN model 1 – SALE 1	NN model 2 – SALE 2	NN model 3 – SALE 3	NN model 4 – SALE 4	NN model 5 – SALE 5	NN model 6 – SALE 6
SALE OF THE PRODUCT GROUP	mean: 783.27, stdev: 254.42	mean: 1394.33, stdev: 434.44	mean: 494.75, stdev: 170.55	mean: 3027.48, stdev: 2947.35	mean: 584.50, stdev: 298.38	mean: 174.29, stdev: 55.20

Table 3. Output variables in all neural network models with their descriptive statistics

Dataset consisted of 143 observations, randomly divided into three subsamples: 60% of data is used for training, 20% for cross-validation, and last 20% for testing keeping the same distribution of output variable in the train and test samples. The three layered backpropagation NN algorithm was used, with sigmoid transfer function and delta learning rule. The learning rate was dynamically changed with the process of learning, and ranged from 0.001 to 0.7. The momentum ranged from 0.1 to 0.7. Overtraining is avoided by a cross-validation procedure which alternatively trains and tests the network until the performance of the network on the test sample does not improve for *n* number of iterations. Number of hidden units ranged from 1 to 20. After training and testing the network on maximum 100000 iterations, all the NN algorithms were validated on the out-of-sample data (20% of the total sample) in order to determine their generalization ability. Root mean square error (RMSE) is used as the evaluation instrument for all neural network models, according to [8]:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=0}^{n-1}(t_i - o_i)^2} \qquad (2)$$

where t_i is the desired output, o_i is the output computed by the network (predicted), while n is the number of observations in the sample. In addition to RMSE, the correlation between desired and computed output is also computed and observed. Separate neural network models are built for each of the six groups of products. The results on the test sample are presented in the Table …

Neural network model	Number of hidden units	RMSE on the test sample	Correlation coefficient on the test sample
SALE1	3	0.0296	0.9938
SALE2	3	0.0025	0.8800
SALE3	7	0.0079	0.9543
SALE4	7	0.0499	0.9904
SALE5	6	0.0366	0.9893
SALE6	3	0.0342	0.9619

Table 4. The results of neural network models for sale prediction

Since the RMSE for all six NN models is very low, it can be stated that the sale for all six groups of products can be effectively predicted by neural networks. The lowest RMSE (0.0025) is obtained for the second group of products (wall paint colors), then for the third group (nitro enamels) 0.0079 where the deviation between desired and predicted sale is less than 1%. Although the NN model for the fourth group of products (one-component enamel mix) produced the highest RMSE (0.049), the deviation is still below 5%, which is acceptable for the majority of practical applications. Correlation coefficient is also very high for all NN models showing a strong connection among desired and predicted output for all six groups of products. Graphical presentation of desired and predicted output enables the analysis of some critical deviations through the test sample. Figure 6. shows such graph of the first NN model – SALE1, indicating that the largest deviations are present at the end of the test sample when the real values of sale were very high, with sharp peaks that NN could not predict.

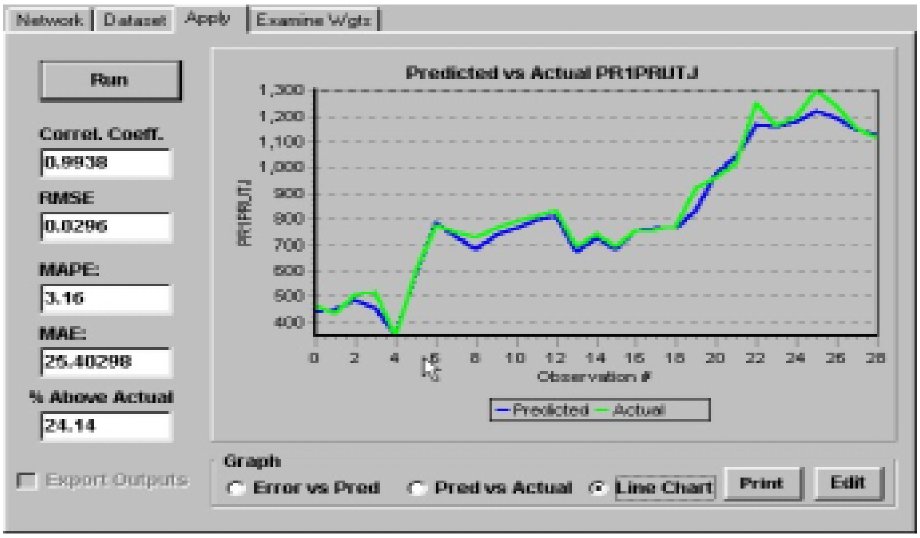

Figure 6. Graph of the desired (actual) and predicted sale in the test sample of the first NN model

According to the above NN results, all six NN models can be effectively used to predict future sale of the each of the six products in a small company. NN methodology showed a very high accuracy with this type of problems, and can be easily incorporated in the intelligent decision support system for small business.

6. CONCLUSION AND GUIDELINESS FOR FUTURE RESEARCH

Rapid development of new information and communication technology enables even small enterprises to benefit from advanced intelligent methods, and therefore gain better position on today's global market. The paper discusses the characteristics of the intelligent decision support system for small business, and its architecture as a preliminary research for building a more detailed concept of organizing decision support systems in small businesses. The IDSS for small business needs to incorporate the following specific characteristics: low cost of implementation and maintenance, high scalability and adaptability, simplicity for usage, modularization, short implementation time, minimal number of data transformation needed, low-risk, and effectiveness. The proposed architecture consists of the basic elements of an IDSS such as data and document management subsystem, the modeling management subsystem, the knowledge management subsystem, the user interface, and the decision maker. It is important to enable the scalability of the data subsystem such that data marts can be used at the starting level of introducing IDSS, and a data warehouse at the growing level. Availability of data mining tools enable the usage of advanced methods even on smaller data sources such as those in small enterprises. Neural networks, together with

other data mining techniques are able to offer effective predictions for small business, in combination with expert system and intelligent agents that will take the role of explaining the results to the decision maker in an understandable language.
For future research we suggest to do the feasibility study of the discussed archictecture in order to obtain more clear picture of its effectiveness and suitability for small business. Since we illustrated only two types of business problems that could be covered by the system, it will be also valuable to set the wider range of problems that will give more insight into the possibilities and limitations of the system. Detailed investigation of all the subsystems of the IDSS, with the focus to the integration of modeling techniques and data interchange is also needed. The lack of developed models for small business problem solving is another reason to do more research in this area.

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