Managerial Decision-making: Measuring and Manifestations of Risks and the Possibilities of their Reducing[1]

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Abstract

The paper is concerned with measuring and assessment of risk scenes in managerial decision-making. It builds upon the uncertainty of economic information, which is converted into the concept of risk scene expressed in terms of probability and using confidence intervals of the predicted quantities. The paper explains the relation of a degree of risk expressed by the classical information measure, bit, by the concept of confidence intervals, or possibly by the standard deviation. When making decisions, the manager is interested not only in the quantitatively expressed value of risk scene with the use of forecasting models, but mainly in the impact of decrease/increase of decision-making risk expressed by the effect, i.e. profit/loss caused by such a decision to achieve targets. A method of decision effect calculation is proposed which is derived from the information entropy change and the change in risk scene in managerial decision-making. Forecasting models are applied which are based on an expert estimate and a statistical theory, and the risk scenes are assessed in forecasting models based on neural networks.

Keywords: *confidence interval, uncertainty, entropy, prediction models, neural networks, managerial decision, risk scene assessment*

JEL Classification: C13, C45, D81, G32

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1. Introduction

Managerial decision-making is a complex issue, the complexity of which is caused by many factors. One of the factors is the way of obtaining information and its credibility for decision-making and operating with them. Every piece of information which the manager has at their disposal is overcast with uncertainty or entropy, as rooted in information sciences. This phenomenon is present throughout the whole process of managerial decision-making. Managers often find themselves in difficult situation due to uncertainty in the decision-making process. They realize the responsibility they have for the consequences of their decisions. The only way of reducing uncertainty of the whole decision-making process is making the information which serves as the basis for making decisions more precise. There is no need to emphasise the fact that using suitable means of making information more precise facilitates decision-making. An important sphere of information necessary for management of economic processes on all managerial levels is the information about the future development of quantities expressed quantitatively, which is used to characterise the state and the development of the object or process. Evidence shows that it is possible to make this information more precise by a suitable choice and use of forecasting models based on statistical methods, soft computing and artificial intelligence methods. In comparison with the manager's expert estimates, these models based on statistical and soft computing methods or artificial intelligence methods are capable of providing information in the form of forecasts of quantities with an acceptable degree of uncertainty. The manager using these forecasts is able to make better decisions, i.e. such decisions whose risks in achieving targets are minimized.

Mathematical statistics (Cox and Hinkley, 1974; Weisberg, 1980) offers the theory of point estimates and confidence intervals. The manager can set and influence the span of these confidence intervals. The confidence interval indicates the span of possible values into which falls the future estimate of the forecasted quantity with the chosen probability defined by the manager. This way the limits of the possible future values are set. Point or interval estimates of the future values of various economic indicators are important for the strategic manager's decision-making. When determining information entropy in decision-making, it is useful to focus on how the confidence interval for the forecasted economic quantity can be made more precise, i.e. narrowed by using the forecasting model. A significant prerequisite for the application of such a model in management is that apart from the increased reliability of decision-making, the model output results in uncertainty reduction, which makes decision-making easier and less weighted with risk. The fact or statement that uncertainty reduction facilitates the manager's decision-making is not sufficient. The crucial factor is how specifically the entropy change manifests itself in the consequences of the decision. Not only will it be “easier” to make the decision, but more importantly the decision will be more effective in the long run.

One of the approaches to understanding uncertainty in forecasting models is understanding it as the standard deviation σ of the forecasted quantity or process (Marček and Babel, 2009; Marček, 2009). The standard deviation as a degree of uncertainty, or risk, of forecasted quantity values estimates is equivalent to the statistical degree of accuracy of the forecast defined as Root Mean Square Error of the forecast (Marček, 2009; Marček and Pančíková and Marček, 2008, p. 193; Marček and Marček, 2008, p. 409). This approach is used with measuring risks of prognoses of many economic and financial forecasting models, and in forecasting models of economic time series, models for managing financial risk (Zmeškal, 2005a, p. 340; Zmeškal, 2005b, p. 270; Jorion, 2006), methods based on the extreme value theory (Havlický, 2008; Medova and Kriacou, 2001), and Lévy models (Applebaum, 2004; Bertoin, 1998), methods to assess and control financial risk (Jorion, 2009), methods based on time intensity models, usage copulas and implementing risk systems (Bessis, 2010).

For management, the approach based on the statistical analysis of the dispersion of the quantity values, or on the standard deviation analysis, is the most comprehensible way of representing uncertainty. It need to be stated that the standard deviation does not reflect entropy in its true substance as uncertainty which is indicated in bits (binary digits). On the other hand, uncertainty is closely related to how precise are the estimates of the future values of quantities that managers have at their disposal. The less precise the estimate, the larger the standard deviation, and the higher the uncertainty that the information is weighted with. This view of uncertainty does not articulate it in its true sense, however, it expresses very well its inner essence and the mutual relation of entropy and decision-making.

The tasks dealing with the influence of information entropy on managerial decision-making have not been described in literature yet. An important prerequisite is whether the calculation of the degree of uncertainty itself has a sufficient informative value for managers in order for them to follow it during the process of decision-making. If it were only a very abstract value insufficiently explained and vaguely described in literature, it would hardly be applied in the process of managerial decision-making, where the data serving as the basis for managerial decision-making must be relevant and clearly presented. Due to the possibility of achieving effects by applying forecasting models in managerial decision-making, an exceptionally interesting, topical and supporting tool offers itself. Our motivation for elaborating it in theory was the fact that to this day there is no theory that would describe the way to reduce or possibly remove uncertainty in management and to use it to calculate effects.

At present, entropy as a quantity is described in several publications. They are publications from the field of physics (Feynman, Leighton an Sands, 1982, pp. 350, 282), information theory (Černý and Brunovský, 1974). Our recent research was concerned with the elaboration of the missing theory of entropy as a category of uncertainty and risk in managerial decision-making. Decision-making is one of the basic human activities, whose quality influences the result of the subsequent activities. Mastering managerial roles is a key factor in the successful achievement of targets.

The objective of the paper is to point out specific outlines of uncertainty and risk categories, determine their content in managerial decision-making as a category which conditions the ways and methods of management not only at the stage of decision-making but also the impacts at the stage of implementation of the decision, where the consequences of these decisions (effects or losses) will manifest themselves. The aim of the paper is also to point out the direct relation between the amount of the removed uncertainty and the quality of the manager's decision.

The issue of measuring risk in management and its accompanying phenomena is divided into four chapters in the present paper. Chapter two is devoted to characterizing risk and its manifestation in decision-making in uncertainty conditions. In the third chapter, a diagram of an uncertainty reduction procedure in the manager's decision-making is designed and characterized. In the fourth chapter, risk reduction with the use of forecasting models based on the classical (statistical) methods and models based on artificial intelligence is documented and assessed. Chapter five summarizes the main topics and results.

2. The Relation between Decision-making with Uncertainty and Decision-making with Risk

Decision making is described in literature (Turban and Meredith, 1991; Turban, Aronson and Ting-Peng, 2004) as one of the basic roles of the manager. Decision-making has a dominant position in management. Implementation of planning, organization, coordination and work with people and the results of these activities are based on decision-making. Managerial decision-making is understood as the reaction of the manager to the incurred problems, i.e. it is a process of analyzing and thinking, the result of which is a decision. There are many approaches to decision-making. Selecting one of them depends on the character of the problem, on the time available, and on the manager's abilities. Herbert Simon (1979) distinguishes two ways of decision-making according to the occurrence of the problem at hand: Programmed decision-making deals with problems that the manager has already dealt with before. These are routine and recurring problems. The process of solving these problems is well-established, it is usually possible to convert in into an algorithm, it is often programmed, and standard procedures are usually used. Non-programmed decision-making deals with problems that the manager has not dealt with before. These are more complex and unique problems. The manager does not know in advance how to proceed, and a creative solution is required of him.

Decision-making on the level of lower management usually involves theories and tools such as linear and non-linear programming, dynamic programming, game theory, queuing theory, inventory theory, probability theory, renewal theory, graph theory etc. Decision making on the level of top management is signifycantly influenced by time. Top management uses tools not only from management but also from other science branches such as mathematical statistics, fuzzy set theory, econometrics, operational research, etc. Top managers use these tools to obtain the most precise estimates of the future development of quantities and processes possible. These estimates represent important information on which managers base their decisions.

Specific choice of tools and models for decision-making depends on whether the manager has precise and complete or imprecise and incomplete information at their disposal. The complexity of managerial decision-making relates to decision-making with incomplete information. Most of the real systems can only be described incompletely, i.e. with information which cannot be formally expressed by unequivocally set parameters. This is uncertain information then. In practice, according to Olej (2003, p. 12), there are mainly two types of such information: According to the first type, uncertain information makes it impossible to exactly determine the future behaviour of the examined system. This type of uncertainty is called stochastic, and it can usually be modelled using the probability theory.

Stochastic uncertainty is concerned with the category of the probability risk, which is determined as a scene in the future associated with the specific adverse incident that we are able to predict it using probability theory and a lot of data (Huang, 2009, pp. 5). In this manuscript, we will concern with this type models, which may be described as follows. Let D be a managerial prediction system including explanatory variables V to explain the behaviour of the variable to be forecast, and faults represented as forecast errors e_t in time t = 1, 2,…n. A risk function R in term of the conceptual model D for having a risk scene can be represented as

$$R = D(V,\ e_t), \qquad t = 1,\ 2,...n$$

To assess the managerial prediction risk R we apply different forecasting models which parameters are estimated by statistical tools.

The second type of uncertainty is connected with the description or formulation of the actual meaning of the phenomena or statements about them. This is semantic uncertainty. Natural language words semantics with uncertainty, i.e. with meanings of words and individual statements not being exact, is typical of natural language. This uncertainty has the character of possibility rather than probability, and it is most often modelled by fuzzy systems (Kahraman and Kaya, 2009; Wu, 2009; Huang and Ruan, 2008; Buckley, 2005; Tah and Carr, 2000). As far as decision-making with risk is concerned, this is the case of decision-making where actual information about real systems is uncertain, and it is not important if the uncertainty is caused by incomplete information about the system's behaviour, or if it is semantic uncertainty. In the further text, in accordance with, the risk connected with managerial decision-making will be modelled using probability models and understood as a statistical term of the expected value between two extreme states of decision, i.e. with full uncertainty and decision with certainty.

3. Managerial Decision-making: Information Uncertainty Reduction

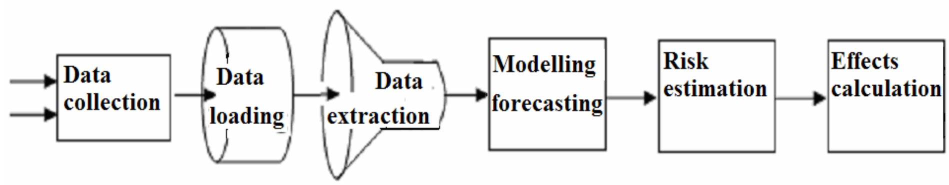
As it was mentioned in the preceding chapter, within the managerial decision--making process uncertainty indicates the degree of risk of achieving targets. Information serves to the manager as the basis for their decisions-making. To minimize the decision risk, i.e. to minimize the negative impacts of the decision and to maximize the benefits of the individual decisions, it is extremely important to get to know the future state of the economic environment. Economic environment on the micro level is characterized by different economic indicators that the manager monitors. The indicators are for example: the development of sales and production of the company and the competitors, the number of competitors, the development of allocation of branches and competing companies, the inflationary trend, the development of wages, the development of prices of raw materials necessary for production, financial markets development, oil and energy prices development, the development of real estate prices, and the currency rate in the countries of sales and business partners. It is impossible to precisely estimate the long-term development of these indicators on the level of strategic decision-making. That is why the decisions are overcast with considerable uncertainty.

There are two ways in which the value of information for the manager is significantly increased. The first way is obtaining the sufficient amount of information in time and with the content that the manager can use for their decision-making. The second way is increasing the precision of the estimates of the future values of quantities and of the output of processes occurring in economy. Every manager can make an intuitive estimate based on their experience by looking at the present and past development. These pragmatic estimates based on monitoring the previous process development offer valuable base information for decision-making. The estimates are also based on the information about the impacts of the factors which affect the development of the monitored process. There can be more of these factors simultaneously. The manager should be able to incorporate the impacts of the factors into their estimate. An estimate obtained this way is in the further text referred to as an expert estimate. Many expert estimates are made without any mathematical or other scientific model procedures or algorithms.

The knowledge and tools of different scientific branches can be used to improve the quality of the decision-making process in strategic management. There are several effective tools which can increase the density of information and thus reduce the uncertainty in decision-making. However, it is not necessary to mention the tools in this context. If information is the main element of decision--making, it is necessary to emphasise obtaining and storing data about the monitored process. Subsequently, the data that will be relevant to the decision-making itself need to be selected. Sometimes it is necessary to obtain such information by extracting it from several kinds of data. Only then follows the elaboration of a prognosis which the manager will be able to use to compare individual solution alternatives and make the actual decision. In the process of decision-making itself needs to be included a quantitative estimate of risk e.g. based on uncertainty, and also the calculation of effect/losses of risk reduction/increase. Such a process of risk reduction in managerial decision-making is represented in a diagram in Figure 1.

F i g u r e 1

A Diagram of Uncertainty Reduction in Managerial Decision-making



Source: Own processing.

The first two blocks in Figure 1 represent activities connected with collecting and storing data. In company information systems such activities are carried out by tools known as ETT (Extraction, Transformation, Transport), ETL (Extraction, Transformation, Loading) tools. Data extraction block. The relevant data extraction block is concerned with obtaining important data and the information about the relations among them. Such information is obtained by statistical analyses known from descriptive statistics and with the support of graphic tools. It is also necessary to eliminate the data which are redundant for the given process. Sometimes this elimination is easy and it can be done pragmatically. At other times it is more complex and the manager cannot reliably determine which type and kind of data will be used in the final forecasting model and which will not. Relying on intuition could be too risky. In such case it is possible to use information systems working on the basis of knowledge mining (Borghoff and Pareschi, 1998; Liebowitz, 1999). These systems enable the manager to extract information from the collected data, and they specify which quantities which are important for management and which are not. In an economic process, which is for example the development of employment, it is possible to monitor more quantities such as the development of tax burden on entrepreneurial subjects, individual political parties preferences, country rating from the viewpoint of attractiveness for foreign investors, level of education, the minimum wage fixed by the government, inflation rate, average savings of citizens, etc. These are cases of prediction models with multidimensional data, where the manager needs to have enough experience to be able to select relevant input of the forecasting systems. The manager can again use the supporting tools working on the principle of „knowledge mining“ (Marček and Marček, 2006, pp. 102, 152; 2009, p. 175; Marček, 2003, pp. 462 – 467).

In the modelling and forecast block, before making the decision itself, the manager must select a suitable forecasting model for determining the forecast. By selecting a suitable forecasting model according to the character of the monitored process, the manager can positively influence the quality of the forecast e.g. by increasing the precision of the prognosis. The manager can be inclined towards a favourite model which they subjectively prefer to the other ones. They can possibly use a single software application which uses only one specific forecasting model to elaborate a forecast. This can be considerably limiting when searching for an optimal forecasting model. In Fraňo (2010, p. 94) can be found recommendations of managers who suggest for every type of process a suitable forecasting model which can best forecast the given type of process.

Risk estimate block is important for comparison of the degree of how the attitude and the situation of the manager is changing during their decision-making.

Risk change (reduction) affects the quality of the decision, i.e. uncertainty reduction must produce the decision effect. Uncertainty and thus also the degree of risk does not have to be expressed numerically, e.g. in bit units, but it can be expressed implicitly if the change shows in effects. In any case, it is better to determine the degree of risks numerically if the decisions are made under the conditions of stochastic type of uncertain information, or verbally if the non-numerical information is formulated in natural language, i.e. in decision-making conditions in which uncertainty has the character of possibility rather than probability. Numerical value of risk scene can be used for comparison of suitability of individual forecasting models or methods which are used to produce forecasts of future values. Different procedures were suggested for calculating uncertainty and thus also risk scene assessment. E.g. in Marček, Pančíková and Marček (2008, p. 191) quantification of uncertainty in forecasting models is based on the analysis of variance forecast errors. In Kahraman and Kaya (2009) the fuzzy set theory is used for calculation of forecast risks, etc. In the following chapter, the procedure for risk scene assessment on the basis of confidence intervals based on the probability is introduced.

The last block in Figure 1 is a block in which effect caused by uncertainty change (benefit or losses) is estimated. Economic quantities such as profit, turnover increase, cost savings or even economy in time are comprehensible quantities for every manager in every sphere of management. These quantities are used to compare individual alternatives of decisions. How the decision effect calculation will follow up the preceding forecast will depend on how costs are determined in a specific activity. The costs function will be different in solving tasks where e.g. stochastic inventory models are used, and it will be different in case of profit calculation in securities trade. A specific way of calculating effects of uncertainty reduction on practical example is given in the following chapter.

4. Reducing Uncertainty with the Use of Forecasting Models and an Effect Estimate in Managerial Decision-making

We will verify the sequence of steps for uncertainty calculation and reduction according to the diagram in Figure 1 by applying it to managerial decision-making at a transport company. Every month a transport company attends to a certain number of transport facilities according to the customer's requirements. It is the manager's task to forecast the number of the facilities and make sure that the company meets the monthly requirements of customers for the capacity of the transport facilities without delays. If the manager underestimated the number of facilities attended to, the prepared machine capacity and the labour capacity would not be utilized. If the manager overestimated the number, the machine and labour capacity of the transport facilities available would not be sufficient. That would lead to delay in attending to them, which would cause service price cut and thus also a reduction in yield.

4.1. Reducing Risk Scene of Managerial Decision-making in Attending to Transport Facilities

In the following section we will give an example of transport facilities number forecasting with ways of assessing risks and effects using forecasting models. On the basis of the obtained prognoses from these models, we will determine their prognostic precision, asses their entropy. In the next sub-chapter we will demonstrate the procedure of quantification of effects arising from the entropy reduction by using different forecasting models.

Managers of transport companies have at their disposal the time series of monthly observation of the numbers of transport facilities attended to in the period from 1990 to 2005, which comprises 192 observations. The development of these values in time is shown in Figure 2. Figure 2 shows that the observed values of the numbers of facilities attended to in the individual months do not prove any irregularities, jumps or periodical variation.

F i g u r e 2

Monthly Numbers of Transport Facilities Attended to from 1999 to 2005

Source: Fraňo (2010), p. 56.

First, based on the development of the observed data, ex-post forecasts of the numbers of the transport facilities attended to in December 1999 and in December 2005 were made. Although these two values are in fact known, their estimates were made because the actual values will be used to compare the precision of the forecast. Forecast estimates were made in two ways for both months. One estimate was made by the manager (technologist) based on their experience from the past development of the values and the knowledge of the technological processes of attending to the facilities. This forecast is marked as an expert estimate. The second estimate was made by neural networks of the perceptron type (Marček and Marček, 2006, pp. 19, 34), (Hertz, Krogh and Palmer, 1991, pp. 89, 115) with the net determination based on the gradient method. The values of these estimates are given in Table 1. Table 1 demonstrates to what degree expert estimates and neural networks estimates approximate the actual values for December 1999 and December 2005.

T a b l e 1

The Actual Values and the Values of the Forecasts of the Number of the Serviced Facilities

Period			
December 1999		December 2005	
Actual value:	33 846	Actual value:	30 621
*Expert estimate:	41 819	*Expert estimate:	29 845

* Expert estimates were made by Technical deputy master, Slovak Railways.

Source: Fraňo (2010), p. 68.

Expert estimates of the numbers of the transport facilities attended to in the individual months in 1999 and in 2005 were then made by a technologist. The results are given in Table 3, columns 3 and 5.

Finally, estimates of prognoses for individual months in 1999 and in 2005 were made with the use of other forecasting models. The calculated MAPE (Mean of the Absolute Percentage Errors) values according to the individual forecasting models in 1999 and in 2005 are given in Table 2. Table 2 shows that the forecasting models based on artificial intelligence (the last three models in Tab. 2) achieve more precise results than the classical forecasting models based on the probability theory.

T a b l e 2

The Mean of the Absolute Percentage Error in the Forecasts with the Use of Forecasting Models in 1999 and in 2005 for the Next 12 Months in %

	Expert estimate	**Regression analysis**	**Expon. smooth.**	**Direct smooth.**	**Winter's algorithm**	**Analogue Complex.**	**Adapt. Algorithm**	**GMDH algorithm**	**Neural network**
1999	34.85	14.91	14.19	17.40	9.14	8.36	13.63	8.54	6.68
2005	6.02	5.27	6.63	18.23	4.99	5.40	4.23	4.15	3.99

Source: Fraňo (2010), p. 90.

The fact that the classical forecasting models are based on the probability theory makes it obvious that the models are affected by stochastic uncertainty. It is natural that mangers try to obtain maximum utilizable information, i.e. the most precise values of the future estimate possible. For the assessment of the estimate uncertainty degree, the method of confidence intervals for point forecasts was used.

With determining forecast confidence intervals based on the classical forecasting models such as the models of regression analysis, exponential smoothing, and Winter's seasonal models is concerned e.g. Gaynor and Kirkpatrick (1994, pp. 385). A more complicated situation is in case of models based on artificial intelligence such as GMDH (Group Method of Data Handling) or the classical neural networks with adaptation of parameters by the gradient method using Back-propagation algorithm. In this case it is possible to test the H_0 hypothesis of the expected type of probability distribution to determine confidence intervals provided that residuals have a normal probability distribution according to Da Silva and Moulin (2000), and this hypothesis can be verified using χ^2 test of good fit on levels of significance set in advance. It is a well-known, widely used and relatively universal method of mathematical statistics (Cox and Hinkley, 1974). To obtain the correct result, it is necessary for the statistical data file to have at least 50 values. For this purpose, in case of using a forecasting model based on neural networks, forecast residuals for the period from 2001 to 2005 were calculated, and thereby we obtained 60 values. These values are given in the appendix. The H0 hypothesis, verified by applying the χ^2 test of good fit on the level of significance $\alpha = 0{,}01$, claims that the residuals of the forecasted values from the actual values can be considered as a data file with a normal probability distribution (Fraňo, 2010, pp. 74 – 75). There are not enough values of statistical data file available in the expert estimates made by the technologist of the transport company for us to be able to say, based on the χ^2 test, if the data file of expert estimates deviations from the facts has a normal probability distribution. However, we do not have enough values to reject the hypothesis either, so to simplify the following calculations, we will presume a normal probability distribution in this case.

The span of the confidence interval is related to the estimate precision. The more precise the input from the forecasting model, the more precisely it is possible to set the span of the confidence interval, and the larger part of uncertainty is removed. Using the χ^2 test of good fit, the H0 hypothesis was verified on the level of significance $\alpha = 0.05$ and $\alpha = 0.01$, and this hypothesis claims that the residuals of the forecasted values from the actual values can be considered as a data file with a normal probability distribution. The confidence interval can be then calculated according to the following expression

$$x \in \left\langle \bar{x} - k_\alpha \ . \ \frac{\sigma}{\sqrt{n}}, \ \bar{x} + k_\alpha \ . \ \frac{\sigma}{\sqrt{n}} \right\rangle \tag{1}$$

where

k_α – the critical value of the standardized normal probability distribution,

α – the level of significance, σ is the standard deviation,

n – the number of observations,

$\bar{x}$ – the expected value.

For the chosen probability P = 0.95, the confidence interval of the expert estimate will have the span $\langle 27352.27, 40339.73 \rangle$. This interval determines the limits which the expert estimate value will not exceed with 95% probability. The value α = 1 − P = 0.05 is the so-called level of significance, which means the probability that a random variable of the expert estimate will acquire a value outside the interval $\langle 27352.27, 40339.73 \rangle$. Analogically, with the probability P = 0.95 was calculated the confidence interval for the expected value of the prognosis by the forecasting model based on neural networks with the values $\langle 31931.73, \ 35760.28 \rangle$.

Interesting about the support of the preference of forecasting models based on neural networks to managers' expert estimates in managerial decision-making is the information about the probability change. The calculation of this probability is possible from expression (1) as the level of significance k

$$k = \bar{x} - a \frac{\sqrt{n-1}}{\sigma_{est}} \tag{2}$$

where

α is the lower limit of the forecast interval of the prognosis calculated by neural network. E.g. in 1999 with the standard deviation

σ_{est} = 10989.64 and expected value (mean) $\bar{x} = 33846$, which was calculated using values in Table 3 is

$$k = 33846 - 31931,72 \frac{\sqrt{12-1}}{10989.64} = 0.5777$$

According to the critical values of the standardized normal distribution, to $k_\alpha = 0.5777$ appertains $\alpha = 0,57$. This implies that the probability that the mean value will fall into the narrower (more precise) interval will change from (1 – 0.577) = 0.423, i.e. from 42.3% to 95%. That is 52.7% growth.

4.2. Entropy as a Measure of Uncertainty

Another measure of uncertainty used in the theory of information is entropy. According to Palúch (2008, p. 21) entropy and also uncertainty is expressed by the amount of information that we get after performing an experiment. For example, if we get a message that an event A has occurred with probability $P(A)$, we also get information $I(A)$ equal $-\log_2 P(A)$ bit.

In case the event A consists of a finite amount of measured events, i.e. subsets of probabilistic space Ω while $A_i \in A$ for $i = 1,\ 2,...n$, $\Omega = \bigcup_{i=1}^{n} A_i$ and $A_i \bigcap A_j = 0$ for $i \neq j$ is valid, then the entropy expressed by Sannon´s definition is Palúch (2008, p. 26).

$$H(P) = \sum_{i=1}^{n} I(A_i).P(A_i) = -\sum_{i=1}^{n} I(A_i).\log_2 P(A_i) \tag{3}$$

In this connection, a very important question is, how will the entropy change if the estimate is more precise? The probability used in the relation for the calculation of entropy is the probability that the estimate value will fall into the narrower 95% confidence interval.

In case of an expert estimate in 1999, this probability is 45%. In case of the prognosis based on the forecasting model based on neural networks, this probability is 95%.

$$H_{\text{expert estimate}}(P) = -\log_2 0.43 = 1.2176 \text{ bit}$$
$$H_{\text{forecasting model}}(P) = -\log_2 0.95 = 0.074 \text{ bit}$$

By using the forecasting model, entropy in 1999 is reduced by 1.1436 bit. Analogically, the entropy values in 2005 are the following

$$H_{\text{expert estimate}}(P) = -\log_2 0.83 = 0.26882 \text{ bit}$$
$$H_{\text{forecasting mode}}(P) = -\log_2 0.95 = 0.074 \text{ bit}$$

By applying the forecasting model in 1999, the entropy value was reduced by 1.1436 bit, in 2005 by 0.19482 bit. In both cases, the application of the forecasting models led to entropy reduction, which makes it possible to make decisions with larger effect. Entropy reduction in 2005 is less substantial than in 1999. That is understandable given the more balanced and more regular development of the time series of the forecasted quantity in the last third of its development, as can be seen in Figure 2. The quantification of the effects brought about by the entropy reduction is important information for making the decision to use the forecasting models. This issue will be dealt with in the next sub-chapter.

4.3. Entropy Reduction and its Relation to Effects

If the application of forecasting models and the ensuing entropy changes had no impact on the effect of the decision itself, the manager would have no practical use for the forecasting models. Because entropy as such is not used much, it would not go beyond the level of mere abstract terminology and empty numbers. The important criterion for choosing the right variant for decision--making is the intended effect. How do we calculate the effect, e.g. as the company profit increment which is brought about by entropy change?

The procedure of the calculation will be described on the example of the transport company management. We will presume that the costs related to providing a service unit are 1 000 SKK. Overestimated forecast will cause tying considerably big capacities to the service provided, but these capacities will not be utilized. Let us presume that the additional costs *Np* related to the overestimated forecast equal one fifth of the costs of service, i.e. *Nn* = 1 000/5 = 200 SKK. The total costs *Tn* related to the overestimated forecast are then calculated as

$$Tn = (\text{forecast} - \text{actual value})\ Nn \tag{4}$$

T a b l e 3

Additional Costs in Using the Individual Kinds of Forecasts in SKK

Month	Actual value	*Expert estimate	Additional cost	Neural network	Additional cost
I.99	23 069	36 271	2 640 400	28 612	1 108 600
II.99	24 989	39 732	2 948 600	29 521	906 400
III.99	28 995	43 989	2 998 800	29 916	184 200
IV.99	28 215	40 300	2 417 000	31 505	658 000
V.99	32 361	43 989	2 325 600	30 601	440 000
VI.99	32 206	40 470	1 652 800	32 497	58 200
VII.99	27 816	41 819	2 800 600	32 040	844 800
VIII.99	33 438	41 819	1 676 200	30 987	612 750
IX.99	33 071	40 470	1 479 800	33 711	128 000
X.99	38 340	41 819	695 800	33 749	1 147 750
XI.99	35 057	40 470	1 082 600	37 055	399 600
XII.99	33 846	41 819	1 594 600	33 499	86 750
Total:			**24 312 800**		**6 575 050**
I.05	29 547	29 347	50 000	31 998	490 200
II.05	28 588	26 764	456 000	31 552	592 800
III.05	31 593	29 845	437 000	32 663	214 000
IV.05	33 729	28 818	1 227 750	33 416	78 250
V.05	32 962	29 347	903 750	33 531	113 800
VI.05	30 975	28 818	539 250	33 925	590 000
VII.05	29 263	29 347	16 800	30 622	271 800
VIII.05	30 815	29 845	242 500	30 785	7 500
IX.05	30 810	28 818	498 000	31 644	166 800
X.05	31 576	29 347	557 250	33 494	383 600
XI.05	31 199	28 818	595 250	31 470	54 200
XII.05	30 621	29 845	194 000	30 445	44 000
Total:			**5 717 550**		**3 006 950**

* Expert estimates are provided by technical deputy master, Slovak Railways.

Source: Fraňo, (2010), enclosure 12.

In contrast with that, in case of an underestimated forecast, a sufficient capacity for carrying out the service will not be available. Let us presume that the additional ensuring of capacity will bring about costs increase *Np* equal to one fourth of the costs of service, i.e. *Np*. = 1000/4 = 250 SKK. The total costs *Tp* related to the underestimated forecast are then calculated as

$$Tp = (\text{forecast} - \text{actual value})\ Np \tag{5}$$

Additional costs incurred by imprecise estimates of the future values are calculated in Table 3.

In Table 3 can be seen that even the additional costs obtained with the use of neural networks have relatively high values. If we compare the additional costs values with the additional costs values of expert estimates, the saving is great. The manager's decision made on the basis of the forecasting model will bring not only entropy reduction but also a considerable costs reduction. In 2005, the differences between the additional costs were smaller. It was caused by a more balanced development of the time series, which was easier to precisely estimate and forecast.

4.4. Uncertainty as the Standard Deviation

In the introductory chapter, we mentioned the possibility of expressing or measuring uncertainty using the standard deviation. We will specify its use on the basis of the results from the examples given in the previous chapters.

The standard deviation is used in literature as the degree of uncertainty and risk (Marček, 2008; Brealy and Myers, 1984, pp. 119, 126, 585). As far as relevancy is concerned, it is probably the easiest and, for managerial practice, the most comprehensible way of expressing and quantification of uncertainty. While the entropy indicated in the information unit bit is at present a still relatively abstract and almost non-used measure for expressing risk in the sphere of managerial decision-making. Uncertainty in the sense of the standard deviation has a higher informative value for managers. Uncertainty expressed by the standard deviation has one drawback, which is unit incompatibility. Entropy is indicated in bits. Despite this fact, as we could see in the given examples, it is easier to work with entropy as the standard deviation. It is possible to state that reduction of entropy of the forecast system was achieved when its standard deviation of forecast errors was reduced. It can be clearly seen in expression (1). In technical systems, rule 3 σ is used which in the figurative meaning provides information about which interval the forecast will almost certainly fall into. Therefore, it provides certainty instead of uncertainty. But it is a certainty which will not push the manager forward with his decision-making if there is a big standard deviation.

The real solution leading to the support of decision-making is reducing uncertainty of the forecast system by using a better forecasting model which will achieve lesser variability of prognosis errors. Described in Marček, Marček and Matušík (2010, p. 1690), on the basis of prognosis errors analysis, is a method of searching for such a forecast horizon for which entropy and thus also prognosis risk is minimal.

Conclusion

In managerial decision-making, risk is the central category based on which the effects of individual variants are assessed, and subsequently the final decision is chosen from several variants. In the present paper we showed the procedure of quantitative assessment of risk scene based on probability terms using confidence intervals for point estimates of economic quantities. We build upon measuring uncertainty based on information entropy indicated in bits and on measuring based on prognosis confidence interval, where uncertainty is expressed in terms of the span of the confidence interval and the probability that by using forecasting model the set prognosis limits around the expected value will not be exceeded. Both approaches to measuring uncertainty were assessed from the viewpoint of utilization in managerial decision-making using forecasting models based on an expert estimate, statistical models, and neural networks models.

Apart from measuring risk, an important factor of using the individual forecasting models for managerial decision-making is quantification of effect brought about by uncertainty reduction. Specific procedure of calculating effect from reducing uncertainty was illustrated by applying the managerial decision-making of a company providing transport services.

The results of the study showed that there are more ways of approaching the issue of measuring risk in managerial decision-making in companies. It was also proved that it is possible to achieve significant risk reduction in managerial decision-making by applying modern forecasting models based on information technology such as neural networks developed within artificial intelligence.

Appendix

Transport Company: Deviation of Forecasts Obtained by Neural Networks Forecasting Model from the Actual Values of the Process for the Transport Company Serving for the Calculation of the Parameters for the χ^2 Test

Month. year	Actual	Forecast	Deviation	Month. year	Actual	Forecast	Deviation
I.01	36 587	39 004	–2 417	VII.03	33 658	32 413	1245
II.01	38 875	36 617	2 258	VIII.03	33 456	37 795	–4 339
III.01	42 454	37 645	4 809	IX.03	32 763	34 961	–2 198
IV.01	38 559	40 649	–2 090	X.03	37 242	33 695	3 547
V.01	40 883	37 940	2 943	XI.03	35 793	35 620	173
VI.01	38 554	38 569	–15	XII.03	31 422	35 058	–3 636
VII.01	38 755	37 913	842	I.04	27 611	33 010	–5 399
VIII.01	33 539	39 606	–6 067	II.04	29 449	30 056	–607
IX.01	38 903	35 319	3 584	III.04	35 139	31 923	3 216
X.01	37 412	38 306	–894	IV.04	32 099	34 679	–2 580
XI.01	38 356	37 138	1 218	V.04	34 755	33 349	1 406
XII.01	35 258	38 462	–3 204	VI.04	33 071	33 415	–344
I.02	29 752	35 757	–6 005	VII.04	34 731	32 393	2 338
II.02	34 555	35 377	–822	VIII.04	33 401	34 194	–793
III.02	37 678	37 411	267	IX.04	32 710	34 048	–1 338
IV.02	34 926	37 020	–2 094	X.04	36 044	34 680	1 364
V.02	34 483	35 732	–1 249	XI.04	34 049	35 268	–1 219
VI.02	35 845	33 015	2 830	XII.04	31 714	34 848	–3 134
VII.02	34 657	34 406	251	I.05	29 547	31 998	–2 451
VIII.02	36 983	36 390	593	II.05	28 588	31 552	–2 964
IX.02	33 274	37 747	–4 473	III.05	31 593	32 663	–1 070
X.02	39 336	33 761	5 575	IV.05	33 729	33 416	313
XI.02	38 203	36 833	1 370	V.05	32 962	33 531	–569
XII.02	33 848	37 575	–3 727	VI.05	30 975	33 925	–2 950
I.03	29 679	35 513	–5 834	VII.05	29 263	30 622	–1 359
II.03	29 733	31 986	–2 253	VIII.05	30 815	30 785	30
III.03	33 973	31 748	2 225	IX.05	30 810	31 644	–834
IV.03	31 808	35 406	–3 598	X.05	31 576	33 494	–1 918
V.03	34 684	33 614	1 070	XI.05	31 199	31 470	–271
VI.03	32 649	35 474	–2 825	XII.05	30 621	30 445	176

Mean value μ is –731.62.

Standard deviation σ is 2649.43.

Variation span of data file is R = 5575 – (–6067) = 11.642.

Source: Fraňo (2010), enclosure 8.

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