Managerial D-M: Measuring of risk scenes and tools of their reducing

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Abstract. The paper is concerned with measuring and assessment of risk scenes in managerial decision-making (D-M). 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. The risk connected with managerial decision-making is modeled using probability models and understood as a statistical term of the expected value between two extreme states of decision. Forecasting systems are applied which are based on the latest statistical theory and artificial neural networks. The degree of risk is assessed. The impact of these methods to risk reduction is judged in managerial decision-making.

Keywords: confidence intervals, uncertainty, entropy, forecasting models, neural networks, managerial D-M, risk scene assessment.

JEL Classification: C13, C45, D81
AMS Classification: 90B50

1 Introduction

An important sphere of information necessary for management of production processes on all managerial levels is the information about the future development of quantities expressed quantitatively, which is used to characterize 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.

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, there are mainly two types of such information. According to the first type, uncertain information makes it impossible to exactly determine the future behavior of the examined system. This type of uncertainty is called stochastic, and it can usually be modeled using the probability theory. 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 modeled by fuzzy systems.

One of the approaches to understanding uncertainty in forecasting models is understanding it as the standard deviation σ of the forecasted quantity or process [7]. 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. 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. 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 D-M.

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

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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 D-M with uncertainty and D-M with risk

As it was mentioned in the preceding chapter, within the managerial decision-making process uncertainty indicates the degree of risk of achieving targets. 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 significantly 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.

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 [3]. 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 behavior of the variable to be forecast, and faults represented as forecast errors e_t in time $t = 1, 2, \dots n$. A risk function *R* in term of the conceptual model *D* for having a risk scene can be represented as

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

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

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 behavior, or if it is semantic uncertainty. In the further text, in accordance with, the risk connected with managerial decision-making will be modeled 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

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. 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.

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.

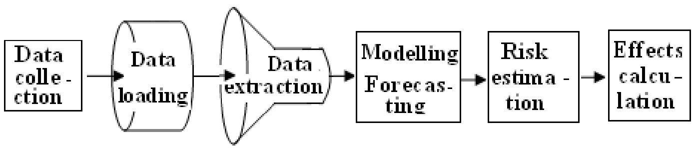

Figure 1 A diagram of uncertainty reduction in managerial decision-making

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. 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.

In the modeling 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.

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. 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 [6]. the quantification of uncertainty in forecasting models is based on the analysis of variance forecast errors, in [4] 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 [1].

4 Reducing uncertainty with the use of forecasting models

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.

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.

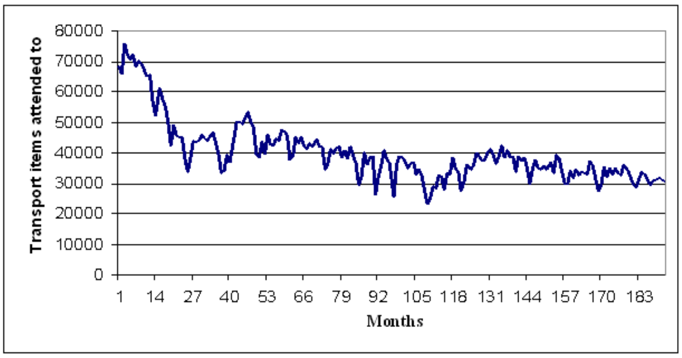

Figure 2 Monthly Numbers of Transport Facilities Attended to from 1999 to 2005

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 [2] 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.

December 1999		December 2005	
Actual value	33846	Actual Value	30621
*Expert estimate	41819	*Expert estimate	29845

*Expert estimates were made by Technical deputy master of the Slovak Railways

Table 1 The Actual Values and the Values of the Forecasts of the Number of the Facilities

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. 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 Table 2) achieve more precise results than the classical forecasting models based on the probability theory.

Year	Expert estimate	Regress. Analysis	Exponent. smoothing	Winter´s algorithm
1999	34.85	14.91	14.19	9.14
2005	6.02	5.27	6.63	4.99
Year	Direct smoothing	Adapt. Algorithm	GMDH algorithm	Neural network
1999	17.40	13.63	8.54	6.68
2005	18.23	4.23	4.15	3.99

Table 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 %

For the assessment of the estimate uncertainty degree, the method of confidence intervals for point forecasts was used. 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, and this hypothesis can be verified using χ^2 test of good fit on levels of significance set in advance. Using the χ^2 test of good fit, the H_0 hypothesis was verified on the level of significance α = 0.05 and α = 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

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

where k_α is the critical value of the standardized normal probability distribution, α is the level of significance, σ is the standard deviation, n is the number of observations, $\bar{x}$ is 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 manager´s 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*

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

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) $\overline{x} = 33846$, which was calculated using estimates of prognoses for individual months in year 1999

$$k = 33846 - 31931{,}73\frac{\sqrt{12-1}}{10989.64} = 0.577.$$

According to the critical values of the standardized normal distribution, to $k_\alpha = 0.577$ 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 [8]. 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 $i = 1,\ 2,\ldots n$, $\Omega = \bigcup_{i=1}^{n} A_i$ and $A_i \bigcap A_j = 0$ for $i \neq j$ is valid, then the entropy expressed by Sannon´s definition is.

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

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%. Then

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

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

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

4.3. Uncertainty as the Standard Deviation

The standard deviation is used in literature as the degree of uncertainty and risk [5]. 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 [7], 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.

5 Conclusion

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.

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.

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