Proceedings of the 33rd European Safety and Reliability Conference (ESREL 2023)
Edited by Mário P. Brito, Terje Aven, Piero Baraldi, Marko Čepin and Enrico Zio

Published by Research Publishing, Singapore.
doi: 10.3850/978-981-18-8071-1_P666-cd

Forecasting Risks Using the Competence of Experts

Vugar Aliyev

AMIR Technical Services Company, Azerbaijan. E-mail: prof.vugar.aliyev@gmail.com

Zurab Gasitashvili
Georgian Technical University, Georgia. E-mail: zur_gas@gtu.ge

Merab Pkhovelishvili
Georgian Technical University, Georgia. E-mail: merab5@list.ru

Natela Archvadze
Faculty of Exact and Natural Sciences, Computer science departament, Ivane Javakhishvili Tbilisi State University, Georgia. E-mail: natela.archvadze@tsu.ge

It is often impossible to build risk prediction models - since it is difficult to obtain and analyze large volumes of data in some subject areas statistics. Therefore, when calculating risks, specialists with high competence are often involved. It is also important to calculate the changes in their competence after each audit, which can lead to a change in the composition of the expert group. The expertise is based on the use of human experience and is carried out with the involvement of experts. It is of great importance both when predicting natural and technogenic disasters, and in the prevention of these disasters due to the maximum possible reduction in risks which is expressed in the calculation of the seismic resistance of buildings and structures. We have developed an expert selection system and subsequently an algorithm for calculating the competence of experts based on their expertise.

Keywords: Expert assessment, expert component, necessary expert, sufficient expert.

1. Introduction

Expert assessments are very useful in areas where there is no large amount of data (or there are no them at all) to be able to use statistics in forecasting. Herling (2016); Prangishvili et al. (2022). The expert assessment is constantly expanding- since this is a very affordable and universal method for obtaining the state of various objects and information processing. Mauro et al. (2005); Simonton (2003). This is often the only way to get the necessary information about objects that do not have the information necessary for the functioning and are characterized by their structural-parametric insecurity. Chogovadze et al. (2020).

Expert judgments are intensively used in forecasting tasks, especially when predicting tectonic natural disasters since statistics in this area are very scarce or it is difficult to obtain and analyze. Aliyev et al. (2022); Gasitashvili et al. (2019); Gasitashvili et al. (2022).

Prediction methods can be divided into intuitive methods and formalized (mainly mathematical) methods. Formalized models are divided into subject models (mechanics, thermodynamics, natural disasters, etc.) and models of time series.

Object-oriented models are mathematical forecasting models that are used to build object-oriented laws. Elawady et al. (2022); Shan et al. (2022). For example, a model used to compile weather forecasts contains the equations of hydrodynamics and thermodynamics. The development forecast of the population is made according to a model built on a differential equation. The prognosis of sugar levels in the human blood suffering from diabetes is based on a system of differential equations. In short, such models use attitudes characteristic of a particular subject. Such models are characterized by an individual approach to development.

Models of time series are models of mathematical forecasting, trying to find the dependence of the future value on the past within the process itself and calculate the forecast based on this dependence. These models are universal for different subject areas, that is, their general view does not change depending on the nature of the time series. Kaur et al. (2023); Jiang et al. (2023); Kumar et al. (2022).

The time series models easily lend themselves to simple division into parts. Yang (2006). The time series models can be divided into two groups: statistical models and structural models. In statistical models , the dependence of the future value on the past is set in the form of a certain equation. Nsubuga (2022); Prajam et al. (2022); Zvikaite et al. (2023). These include:

- regression models (linear regression, nonlinear regression);
- Autoregression models (Arimax, Garch, ARDLM);
- model of exponential smoothing;
- a model based on a sample of maximum similarity;
- etc.

In structural models the dependence of the future value on the past is set in the form of a certain structure and rules of movement on it. Hajirahimi and Khashei (2022); Ding et al. (2022); Huang et al. (2022). Wang et al. (2022). These include:

- neural network models;
- models based on Markov's chains;
- models based on classified regression trees;
- etc.

However, there are a large number of models for forecasting temporary rows that are used to compile forecasts, such as SVM models (support vectors), GA models (genetic algorithm), and many others.

To date, there are quite a lot of forecasting models that allow them to analyze them to increase the accuracy of forecasts of models, which further increases the relevance of the topic under discussion.

Due to the lack of data, the lack of large amounts of data in solving geophysical problems (specifically, earthquake forecasting) does not allow the use of classical methods of statistical analysis. This attaches great importance to expert assessments, their correct choice, and the correct use of their rating. Zavyalov and others (2022).

When forming expert assessments, an expert is used as the main source of information, and it is necessary to attract those experts who have sufficient specific knowledge and great experience that can be used to solve specific problems in a fairly short time and with minimal costs. With great accuracy to improve the quality of an objective assessment, it is necessary to attract as many experts as possible, and when making a decision, it is advisable to take into account the informed opinions of experts. Janssen et al. (2013).

An urgent problem is to increase the reliability of expert assessments by attracting more competent experts to the group. This leads to the implementation of special conditions when choosing the composition of experts precisely their professional competence to insure against gross errors due to the fault of incompetent experts. Shanteau (1992); Jones and Moore (2006); Mednikova and Mednikov (2018).

2. The selection of experts

The problem of selecting of experts for the expertise is one of the most difficult expert research in theory and practice. As experts, it is necessary to use the most competent specialists whose decisions will help managers to make adequate and acceptable decisions. Our goal is to determine the rules for selecting n experts with the maximum competence coefficient for the tasks of forecasting and determining the weights.

As we have already mentioned, first it is necessary to solve the problem of choosing experts, determine their competence and determine the optimal number of experts. To determine the competence of experts, the following data will be accepted: the level of education, experience, experience expertise performed by the profile, the degree of expert, and the number of scientific works on the profile in recent years (3-5 years). Each of these factors should have reasonable weights, the amount of which determines the competence of the expert, and the initial weight for each expert is calculated.

3. Tasks that need to be solved during the expertise

Despite the variety of subjects of expertise and forms of conduct, the result of the work of experts is either the generation of new options for evaluating the forecasts of events or the solution of assessment problems.

The generation of new alternatives can occur, for example, as one of the proposals of experts. Then a new consideration may be required to account for newly emerging options.

In most cases, the result of the work of the expert group may be a solution to the problem of evaluating one of the options: measurement, ranking, and/or classification. Measurement is an operation that determines the ratio of one (measured) value to another value adopted by one. With this ratio, the numerical value of the measured value is obtained. In the process of conducting the expertise, experts may be proposed to evaluate the measured value in a certain range of values and with a certain value.

The result of the work of experts to solve the problem of ranking may be the distribution of alternatives or their components in terms of their importance.

The solution to the problem of classification is to divide objects into classes, and the expert is in the process of studying the objects proposed to him and connecting them with the class system presented to him.

Methods for processing the results of the expert assessment are usually based on statistical assessment methods. In preparation for the expertise, one of the known methods is chosen in advance or invented on its own. For example, such methods may include: calculating the average value of assessments, calculating the median, calculating the maximum, and others, depending on the peculiarities of the task under consideration.

4. Description of experts

The form of expertise can be very different, but, as a rule, it is based on an expert survey. A questionnaire or a set of questions has been developed that the expert should answer.

Structurally, the questionnaire issues should be logically related to the central task of the expertise. The system of questions in the questionnaire must meet the following two requirements:

- The response of the expert yes/no (or 1/0);
- The expert's response is given in the form of a numerical value in %.

The example discussed below relates to the task of predicting earthquakes. 10 people take part in the audit. Each of them replied whether an earthquake will occur in a particular area, for example, in a racha, in a certain period of time (see *Table 1*).

N of experts	Competence	Event prediction (yes/no)
1	7.2	0
2	8.1	0
3	7.7	1
4	9.5	0
5	7.5	1
6	8.5	1
7	8.1	0
8	9.4	1
9	8.0	1
10	9.2	1

Table 1 . Questionnaire about earthquake occurrence in region Racha (Georgia)

The questionnaire on the occurrence of an earthquake in the Racha (the region of Georgia) district as a whole when preparing the expertise should be developed as a methodology for evaluating the questionnaire, as well as a methodology for determining the aggregate assessment. The decision on whether the predicted event will occur or not is made based on what is more: the amount of the components of experts who positively answered the question of what the event will happen or the amount of the components of experts who predicted that the event will occur. The event will not happen. In the case of this example, we consider two amounts: the sum of the competencies of those experts who answered "yes", and the second - "no". We denote these amounts as Sum_1 and Sum_2. These variables are calculated as follows:

$$Sum_1 = 7.7 + 7.5 + 8.5 + 9.4 + 8.0 + 9.2 = 53.2$$

$$Sum_2 = 7.2 + 8.1 + 9.5 + 8.1 = 32.1$$

As $Sum_1 > Sum_2$, therefore, It is possible to conclude that the predicted event will occur according to a panel of experts.

Consider the second case when the expert determines the forecast of the event in %. Suppose N experts are chosen, the competencies of which: $c_1, c_2, \dots, c_n$. The questionnaire contains a question for which each expert gives forecasts: $P_1, P_2, \ldots, P_n$ (given in %). Table 2 shows an example with the participation of 10 experts:

N of experts	Competence	Event prediction (%)
1	7.2	59
2	8.1	78
3	7.7	72
4	9.5	75
5	7.5	34
6	8.5	77
7	8.1	45
8	9.4	81
9	8.0	92
10	9.2	55

Table 2. An example when experts determine the answers as a percentage

Calculate the following value:

$$R = (c_1 * P_1 + c_2 * P_2 + \cdots + c_n * P_n)/m$$

where m is s the sum of the competencies of all experts.

R=$(7.2 * 59 + 8.1 * 78 + 7.7 * 72 + 9.5 * 75 + 7.5 * 34 + 8.5 * 77 + 8.1 * 45 + 9.4 * 81 + 8 * 92 + 9.2 * 55\ )\ /$ (59+78+72+75+34+77+45+81+92+55)= 5600.90 / 83.20 = 67.32.

The obtained value determines that there is a 67.32 % probability that the event will occur. Earthquakes rarely happen. If an earthquake occurs, then those experts who did not predict the occurrence of the earthquake will be removed, and other experts will be added based on their competence. At the same time, we get a new group of "necessary" experts.

5. The division of experts into "necessary" and "sufficient" groups

We can evaluate experts on how they predict the occurrence event, that is, you can assign a score to each expert - the number of events predicted by him, divided by the number of events. We introduce the concept of "The probability of justification of the expert" into the forecasting system - for this predicted event, this value should indicate the number of predicted events guessed by a specific expert in %. The probability of excuses for the expert is calculated by the formula: Gasitashvili et al. (2022)

$$K_i = \frac{m}{p_i} 100\%,$$

where m is the number of events, P_i denotes the number when A_i expert predicts the event.

Suppose there is a prediction of a certain event $A_{1,} A_{2,} \ldots, A_n$ experts where n denotes the number of experts. Each expert can be called a "necessary" expert if he always predicts an event, although he makes predictions that do not come true. If an expert cannot predict all the events that will occur, he cannot be considered a "necessary" expert. A "sufficient" expert is an expert whose forecasts always come true, but he cannot predict all the events that will occur. It goes without saying that if there is only a "sufficient" number of experts in the expert group, it may happen that all events will be predicted by this group as much as possible.

Methods for processing the results of expert assessment are usually based on statistical assessment methods. In preparation for the expertise, one of the known methods is chosen in advance or invent their own. For example, such methods may include: calculating the average value of assessments, calculating the median, calculating the maximum and others, depending on the peculiarities of the task under consideration. In addition, it is necessary to evaluate the assessment error, which is the average quadratic deviation of expert assessments.

Consider the algorithm for assigning a rank to each expert when he is included in the group of "necessary" experts and when the request requires a logical type of response. The first invited expert, for whom the rating is not yet calculated, is naturally assigned to rating value 1. In the future, his rating is calculated according to the formula specified by the formula for calculating the probability of justification, but if the expert cannot predict the event, this expert is excluded from the group of "necessary" experts.

In the case of the second type of question, the expert rank is determined by how closely the value indicated by him is to the average value. If it is close, you should increase the rating by 1, if a little far, then the rating should be left unchanged, and those experts who have an error, reduce the rating. Naturally, according to reports, some specialists can be completely excluded from the list of experts in this field and will no longer be invited.

For *Table 2,* with a result calculated by the formula (value 67,32), the values of the 3th and 4th experts are closest to the module (4,68 and 7,68), therefore it is concluded that the rank of the 3th and The 4th expert must be increased. The greatest deviation from the exact passage, which the 5st and 9th experts have and, accordingly, will be reduced, will also be calculated. As soon as the expert rank is approaching 0, this expert will be replaced by another expert. See the results obtained in *Table 3*:

N of experts	Competence
1	7,20
2	8,10
3	8,70
4	10,50
5	6,50
6	8,50
7	8,10
8	9,40
9	7,00
10	9,20

Table 3. Competence of experts after change

If the expert gives an incorrect forecast, we discard it before the next event occurs, and in the same way, new experts can be added to a sufficient number of experts.

6. Results

Thus, 2 options are used to calculate the forecast of events: when experts determine whether an event will occur or not, and the second option - is when experts determine the interest of the event.

The data was introduced to determine the initial competence of the expert, and subsequently the algorithm for changing its competence.

The concepts of “necessary” and “sufficient” expert are defined. How to change experts when the event is the onset and how to calculate the probability of an event.

References

Aliyev, V., Z. Gasitashvili, M. Pkhovelishvili, N. Archvadze. (2022). Algorithm for building a hybrid model of the existing risk model. *Reliability: Theory and Applications*, 17, pp. 106–110.

Chogovadze, G., G. Surguladze, N. Topuria, N. Archvadze. (2020). Implementation of a prediction model with cloud services. *Bulletin of the Georgian National Academy of Sciences.* 14(3), pp. 29–35.

Ding, S., Z. Tao, H. Zhang, Y Li. (2022). Forecasting nuclear energy consumption in China and America: An optimized structure-adaptative grey model. *Energy*, Elsevier.

Elawady, M., A. Sarhan, MAM Alshewimy. (2022). Toward a mixed reality domain model for time-Sensitive applications using IoE infrastructure and edge computing (MRIoEF). *The Journal of Supercomputing*, Springer.

Gasitashvili, Z., M. Pkhovelishvili, N. Archvadze, (2019). Prediction of events means of data parallelism. *Proceedings - Mathematics and Computers in Science and Engineering, MACISE 2019*, pp. 32–35, 8944725.

Gasitashvili, Z., M. Pkhovelishvili, N. Archvadze. (2022). Reducing risks through improvement of preduction models. *Reliability: Theory and Applications,* 17, pp. 197–202.

Hajirahimi, Z., M. Khashei. (2022). Hybridization of hybrid structures for time series forecasting: A review. *Artificial Intelligence Review*, Springer.

Herling, R. (2016). Operational Definitions of Expertise and Competence. *Advances in Developing Human Resources.*Volume 2, Issue 1.

Huang, W., H. Wang, H. Qin, Y. Wei, J. Chevallier. (2022). Convolutional neural network forecasting of European Union allowances futures using a novel unconstrained transformation method. *Energy Economics*, Elsevier.

Janssen, J., Slavi Stoyanov, Anusca Ferrari, Yves Puni e, Kees Pannekeet, Peter Sloep. (2013). Experts' views on digital competence: Commonalities and differences. *Computers & Education*, Volume 68, October 2013, pp. 473-481.

Jiang, F., Z Zhao, X Shao. (2023). Time series analysis of COVID-19 infection curve: A change - point perspective. *Journal of econometrics*, Elsevier.

Jones, L., Rob Moore, (2006). Education, Competence and the Control of Expertise. *British Journal of Sociology of Education.* Volume 14, 1993 - Issue 4, Pages 385-397. Published online.

Kaur, J., KS. Parmar, S. Singh. (2023). Autoregressive models in environmental forecasting time series: a theoretical and application review. *Environmental Science and Pollution*, Springer

Kumar, R., P. Kumar, Y. Kumar. (2022). Multi-step time series analysis and forecasting strategy using ARIMA and evolutionary algorithms. *International Journal of Information,* Springer.

Mauro, N., Teresa M.A. Basile, and Stefano Ferilli. M. Ali and F. Esposito (Eds.). (2005). GRAPE: An Expert Review Assignment Component for Scientific Conference Management Systems. *IEA/AIE LNAI* 3533, pp. 789–798, 2005. Springer-Verlag Berlin Heidelberg 2005.

Mednikova O.V., Mednikov D.A. (2018). Characteristics of tool programs in the design of expert systems. *Bulletin of the Moscow International Academy*. No. 1. pp. 114-117.

Nsubuga, P. (2022). A demand forecasting model for various categories of perishable items. dissertations.mak.ac.ug

Prajam, S., C. Wechtaisong, AA. Khan. (2022). Applying machine learning approaches for network traffic forecasting. *Indian Journal of Computer Science* , jcse.com

Prangishvili, A., Z. Gasitashvili, M. Pkhovelishvili, N. Archvadze. (2022). Predicting Events by Analyzing the Results of the Work of Predictive Models. *Communications in Computer and Information Science*, 1562 CCIS, pp. 64–78.

Prangishvili, A., Z. Gasitashvili, M. Pkhovelishvili, N. Archvadze. (2022). Predicting Events by Analyzing the Results of the Work of Predictive Models. *Communications in Computer and Information Science,* 1562 CCIS, pp. 64–78.

Shan, D., Z Zhao, J Quan, Q Yu, Y Lan. (2022). Research on multi-physical domain modelling and simulation technology of electromechanical system based on bond graph. *IET.*

Shanteau, J. (1992). Competence in experts: The role of task characteristics. *Organizational ehavior and Human Decision Processes,* Volume 53, Issue 2, November 1992, pp. 252-266.

Simonton, D. K. (2003). Expertise, competence, and creative ability: The perplexing complexities. In R. J. Sternberg & E. L. Grigorenko (Eds.*), The psychology of abilities, competencies, and expertise*. pp. 213–238. Cambridge University Press. https://doi.org/10.1017/CBO9780511615801.010

Wang, Y., L. Ye, Z. Yang, X. Ma, W. Wu, L. Wang. (2022). A novel structure adaptive fractional discrete grey forecasting model and its application in China's crude oil production prediction. *Expert Systems with* , Elsevier.

Yang J. M. Sc. (2006). Power System Short-term Load Forecasting: Thesis for Ph.d degree. *Germany, Darmstadt, Elektrotechnik und Informationstechnik der Technischen Universitat*, 139 p.

Zavyalov A.D., Morozov A.N., Aleshin I.M., Ivanov S.D., Kholodkov K.I., Pavlenko V.A. (2022). Medium-term earthquake forecast method «Map of expected earthquakes» (MEE): Results and prospects, Geofi zicheskie Protsessy i Biosfera (Geophysical Processes and Biosphere), vol. 21, no. 2, pp. 114–131 (in Russian). English version: *Izvestiya, Atmospheric and Oceanic Physics,* 2022, vol. 58. ISSN: 0001-4338 (Print), 1555-628X(Online).
https://link.springer.com/journal/volumesAndIssues/1148

Zvikaite, G., S Moore, O McDermott. (2023). Implementing a Forecast Methodology as a Precursor to Lean Management. *Green and Sustainability: 8th IFIP WG,* Springer.