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# Decision support system for analysis of actuarial risks. Literature review.

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***Abstract:*** *Insurance companies are vulnerable to insolvency if the actuarial risk has not been properly calculated. Actuaries, who work in insurance companies, determine actuarial risk. Their task is to set insurance premiums at a rate that ensures the receipt of sufficient money.While making judgments on the resolution of poorly organized or unstructured problems, taking into account various forms of uncertainty, decision support systems are intended to assist and support various types of human activity. With restricted resources, they enable loss minimization. Three methods were analyzed, which would be appropriate for implementation in analysis of actuarial risk.*

***Key words:*** *Actuarial Risk, Decision Support System, Generalized Linear Models, Bayesian networks, Neural Networks.*

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## I. Introduction

Actuarial risk is an insurance term that refers to the probability that an adverse event may occur at a rate that is not proportional to the probability of its occurrence. The essence of the danger in this scenario is that the insurance business may be at risk, in case of an occurrence. A well-run company is aware of the risks it may face and actively manages them on a daily basis. Yet, purchasing too much insurance might result in the wasteful use of resources; conversely, purchasing too little insurance could jeopardize an organization's capacity to remain financially viable. Actuaries, who work in insurance companies, determine actuarial risk. Their purpose is to set insurance premiums at a rate that ensures they receive enough money so that insurers can settle any claims and remain profitable in the process. Insurance companies are vulnerable to insolvency if the actuarial risk has not been calculated appropriately. Actuaries are trained to use several factors to determine the amount of risk to people or things that are the subject of insurance.

When necessary, actuarial risk analysis may include several decades in the future in addition to short-term timestamps. Decision makers can better comprehend the typical range within which outcomes are likely to lie and the potential effects of more extreme events by concentrating on understanding long-term repercussions.

Taking into account the crisis economic phenomena that arose as a result of the aggravation of the political situation and the sharp depreciation of the national currency, the insurance market of Ukraine (life insurance) has undergone significant changes.

A sharp decrease in the purchasing power of the national currency and the establishment of temporary management in most banks with an assessment of "insolvency" were the result of a sharp increase in the degree of distrust of customers towards accumulative life insurance. At the same time, such crisis phenomena became an incentive to strengthen the management of the insurance sector, and to direct attention from accumulative insurance to life insurance.

Achieving realized goals requires instrumental means to minimize the growing costs of limited available resources. The need for such tools has given a resaon, within the framework of methods and systems of artificial intelligence, to a whole range of information technologies designed to help in the management of society, business, the economy and the banking sphere. Many methods for building decision-making systems emerged as a result of the automation of decision-making support procedures. Modern mathematical decision-making techniques, different mathematical models, and technological and software tools are all applied in Decision-Support Systems (DSS).The systematization of current methods for developing DSS enables the assessment of the benefits and drawbacks of such systems and the forecasting of future advancements in this field based on contemporary promising innovations and trends in the use of man-machine systems.

DSS is viewed as an interactive, computer-assisted system (software complex) that supports different sorts of human activity in decision-making connected to the resolution of poorly or unstructured situations. When making judgments in complex situations, the application of DSS offers a full and objective investigation of the topic area. These systems give access to information from sources outside the company and allow decision-makers to look up pertinent data produced by transaction processing systems and other internal information sources.

A decision is defined as a reasoned series of actions taken by the person making the decision. Action goals are directed at an item or control system, and a sequence of actions provides a means of bringing this object or system to a desired condition or achieving a specific goal.

The widespread use of intelligent data processing and decision-making techniques, as well as interface design based on the concepts of intellectualization of the user-system interaction process, are characteristics of contemporary intelligent decision support systems. The term "intellectualization" specifically refers to the system's adaptation to the user's response and preferences regarding the methods of presenting the results of data processing, as well as the user's selection of a method for entering, editing, and replenishing knowledge and data bases that is practical for them. Intelligent DSS are a large and very practical class of information computing systems for data processing that permit the blending of heterogeneous data.The following are examples of intelligent methods and algorithms for data searching and processing: algorithms for data searching with given characteristics, algorithms for bringing data to a specific form, game methods for data searching and processing, and ways of presenting knowledge in the knowledge base. Other planning techniques, approaches to handling uncertainty, neural network-based decision-making techniques, probabilistic models and judgments, clear and fuzzy logic, learning techniques based on prior knowledge and observations, probabilistic approaches to processing linguistic information, etc. are also included in this class of methodologies.

Several methods may be used while developing a DSS. The chosen DSS architecture can be matched with the current DSS needs by conducting a system analysis of these methods. DSS design include specifying the kind of architecture, going into additional depth about the key features of the data processing system, and producing DSS outcomes. The selection and description of algorithms in accordance with data processing techniques, formats, and ways of presenting data and knowledge that may be utilized in DSS serve as the foundation for the creation of a data processing system and the generation of results. The roles of the system for displaying results, the format of presenting data, and the outcomes of data processing, etc., are significant at the final stage of design. The design of the DSS architecture is based on taking these challenges into account.

## II. Methods

### 2.1 Generalized linear models (GLM)

Generalized linear models (GLM) give a simple and robust way to make an analysis of the effect of a large number of factors during the observation of some event. It will take into account all possible correlations in data. The solution method of GLM is more efficient in technical sense than iterative standard methods, which is not only elegant in theory but also important in practice. In addition, this approach provides statistical diagnostics, which helps in selecting only significant variables and in testing hypotheses about the model.

The GLM includes a wide range of models, with the linear regression model being one of many particular cases. The latter's assumptions, which often include normal distribution, constant variance, and additive effects, are disproved.

The target variable can be chosen from an exponential family of distributions, according to D. Anderson et al. [1].

The exponential family of distributions has the general form::

$$f_i(y_i, \theta_i, \varphi) = \exp\{\frac{y_i\theta_i - b(\theta_i)}{a_i(\varphi)} + c(y_i, \varphi)\} \tag{1}$$

where$a_i(\varphi)$, $b(\theta_i)$, та $c(y_i, \varphi)$ arefunctions, that are defined at the beginning;
$\theta_i$is a parameter related to the mean value;
$\varphi$is a scale parameter related to variance.

The variance and the distribution's mean are both subject to change. The impact of explanatory factors is believed to be cumulative on an extra scale. For GLM, the following assumptions are made:

1. **Stochastic component:** each component of Y is independent and is taken from the one distribution of exponential family.
2. **Systematic component:** $p$ covariates(explanatory variables) form linear predictor$\eta$:

$$\eta = X\beta \tag{2}$$

3. **Link function:** the relationship between the random and systematic components is established through a link function that is differentiable and monotonic:

$$E[Y] = \mu = g^{-1}(\eta) \tag{3}$$

There are two information criteria for model selection, according to S. Noora [2], and they are based on likelihood functions and applications, which are issues based on parametric models.
1) Akaike information criterion (AIC).
This method is often used to choose the model with the lowest AIC, which is calculated as

$$AIC = 2k - 2\ ln(L) \tag{4}$$

where $ln(L)$is the maximal log likelihood of the model given "m" observations;
$k$–model's dimension.
Given that the likelihood function's value is multiplied by two without taking into account the second component, the model with the lowest AIC also has the highest likelihood function value.
2) Bayesian information criterion (BIC)
It is a common model selection principle as well. The model is chosen as a formula that minimizes in the next way:

$$BIC = k \log n - 2ln(L) \tag{5}$$

E. Ohlsson and B. Johansson [3] pointed out that it has been the standard rate making tool for insurance since the 1990s'.
N. Naufal, S. Devila and D. Lestari[4] in their work demonstrated that according to the experiments and argumentations, gender is the most influential feature in underwriting factor. The issue of age and smoking status is irrelevant to the likelihood of death. Relation between age and gender was not detected and relation between gender and cigarette smoking status was not detected too.

A. Omerašević and J. Selimović[5] used data mining methods for building model of prediction for non-life insurance premium pricing to select the risk factors that affect the level of the insurance premium. They implemented Forward stepwise regression, CHAID decision tree, C&RT decision tree and neural networks. Methods of data mining for choosing factors help in getting optimal set of predictors with by reducing dimensionality. It helps to make easy explanation of model results, minimize time for fitting the model and prevent from spending a large amount of time on setup of parameters. The analysis of methods was made on claims frequency and claims severity, which were target variables. Forwarded stepwise regression demonstrated awesome results and furthermore, it was the easiest model to implement. It has detected a large amount of risk factors for response variables and outperformed standard method of fitting GLM. Other data mining methods for choosing important risk factors demonstrated acceptable results in context of improving performance of forecast. Methods for selecting risk factors help actuaries to avoid adverse moments, when important risk factors was not included.

M. H. M. A. Siddig [6] pointed out that actuaries must pay big attention on rating system for calculation of premiums from policyholders. In case of overchange in non-life insurance may leave. But on the other hand, choosing wrong rating system may lead to bad risk. The ultimate evaluation is to determine how precisely the system of ratings represents the observed losses. The accuracy of the rating system may be greatly improved by categorizing the observed losses according to the relevant risk factors, since this will reveal exactly which level of each risk factor results in the largest loss (and hence the highest premium) and which generates the smallest loss (to be charged the lowest premium). Many insurance companies use Bonus-Malus system to make a classification about losses. It is a system, where a year without any claims gives a bonus or discount in the premium. On the contrary, year with bad claim bring up increasing amount of premium. Actuaries must be informed about the concept of "The danger of the one-dimensional analysis". The actuary should resist the urge to stop the study after they have determined the average reactions each risk factor in the portfolio causes. The reason is that some risk features tend to be correlated. Thus, actuaries can be tempted to one-dimensional analysis.

S. Kafková and L. Křivánková[7] applied GLM for estimation of annual claims in vehicle insurance. Their result has demonstrated significance of three features like policy holder, vehicle age and area of residence. On the other hand, features like gender or vehicle body type had less importance for analysis.

To explore the risk elements behind the life insurance underwriting risk, R.Cerchiara , M. Edwards and A. Gambini[8] developed a GLM technique, which is frequently employed in general insurance.Moreover, this approach helps with the generation of pertinent sensitivity tests and the calibration of internal models for the stochastic modeling of lapse risk by providing a better understanding of the expected variability in the decrement rates.The results of conducted experiment show the sensitivity of lapse rates to exposure year, product class, and policyholder age while also reiterating the significance of policy term. Although this specific case study demonstrated that the impacts of exposure time and year were mostly agnostic to product class, it's possible that other businesses' experiences might not support this conclusion.

L.Sarul and M.Balaban[9] proved that GLM is an effective tool for assessing non-normal data. As a result, a useful model that uses GLM to account for risk characteristics for the people in the portfolio has been developed. By calculating the coefficient of variation, variety according to the ranges of claim amounts, and the maximum, minimum, and average of the claim amounts, risk was assessed.

On the other hand, not all variables can be included to models. M. Goldburd et al. [10] note that territories are not a good fit for a GLM. Using large numbers of countries or cities may lead to inaccurate results. The solution for this problem is spatial smoothing. J. Yao [11] demonstrated that GLM can sometimes underestimate premiums in segments where the model is highly uncertain. They can be adapted to specific segments, where they are relevant to future sales. Limitations must be included so insurance companies could make the correct decision.

**2.2 Bayesian Networks**

Bayesian Networks represent graphical models of events and processes based on the combination of events and processes based on the combination of some results of probability theory and graph theory. They are closely related to influence diagrams that can be applied to implement decisions. Due to the presentation of interaction between factors of process in the form of cause-and-effect relationships in this model, the highest level of visualization is achieved and, furthermore, a clear understanding of the essence of the interaction of factors of process among themselves. In addition, the main advantage of Bayesian networks is the ability of taking into account statistical and structural uncertainties. This play an important role, because it helps in forming a conclusion with applying exact and approximate methods.

For analyzing processes of many kinds, human behavior, and the operation of technological systems, Bayesian networks may be used to take into consideration and utilize any input data, including expert opinions and statistical data. Networks may employ both discrete and continuous variables, and they can receive input in real time or as statistical databases and information arrays for analysis and decision-making. The maximum degree of visualization is accomplished and, as a consequence, a clear comprehension of the core of the interaction of process factors among themselves thanks to the display of the interaction between process factors in the network as cause-and-effect linkages.This sets Bayesian networks apart from other techniques for intelligent data processing. The capacity to account for statistical, structural, and parametric uncertainty, create models in the presence of hidden peaks and partial observations, and draw conclusions using a variety of approaches, both approximate and accurate, are further benefits of Bayesian networks. In general, Bayesian networks are a high-resource method of probabilistic modeling of processes of arbitrary nature with uncertainties of different types, allowing for the possibility of a sufficiently accurate description of their functioning, evaluation of forecasts, and creation of a management system.

When studying processes of an arbitrary nature, constructing alternatives, and making decisions, the logic of a decision-activities maker's is perfectly consistent with the technique of Bayesian data analysis and expert assessments. A posteriori probabilistic conclusions are drawn about variables, parameters, states, situations, etc. based on combined knowledge and data and are supported by experimental data, additional information of a qualitative or quantitative nature that can be obtained from various sources, and a priori knowledge about the investigated process. In all levels of data analysis, including modeling, forecasting, and decision-making, Bayesian approaches are effectively used.

The sample space of occurrences, as mentioned by R. E. Neapolitan [12], (or collection of events) in random experiments is denoted by the letter $\Omega$. Every conceivable value of the random variable is present in this sample space.Events are known as observations in time series analysis and many other subjects.

Consider two events $A \in \Omega$ and $H \in \Omega$, which are an observation and a hypothesis, respectively.After an event $H$ has already happened, the Bayes formula is used to determine the likelihood that another event $A$ will also occur.Specifically, to determine the conditional probability $P(A|H)$ of $A$ given a certain occurrence $H$.
The ratio of the likelihood of occurrences $A$ and $H$ taken together $P(E \cap A)$ to the probability of event H is known as the conditional probability $P(A|H)$, as long as it is not equal to zero:

$$P\ (A|H) = \frac{P(A \cap H)}{P(H)} \tag{6}$$

Same case for event $H$:

$$P\ (H|A) = \frac{P(H \cap A)}{P(A)} \tag{7}$$

Then Bayes Rule can be rewritten in the next way:

$$P(H|A) = \frac{P\ (A|H) * \ P(H)}{P(A)} \tag{8}$$

This statement depicts the causal connections between the data and the hypotheses. The probability $P(H)$ and $P(A|H)$ are determined a priori, or before any observations are made. The posterior is the probability $P(H|A)$.

The benefit of the Bayesian approach is that a priori probabilities may be adjusted to reflect the actualities of the process being investigated. The probability of occurrences when new information is obtained can then be specified.The theory of Bayesian network formation bases its basic presumption on the idea that events are exhaustive and do not overlap.

$$\bigcup_{j=1}^{m} H_j = \Omega \tag{8}$$

The probability of occurrence A may be determined using conditional probabilities if following criteria are true:

$$P(A) = \sum_{j=1}^{m} P(A \cap H_j) = \sum_{j=1}^{m} P(A|H_j) * P(H_j) \tag{9}$$

Formula (9) may be changed by inserting (10) to get the expression

$$P(H_j|A) = \frac{P(A|H_j) * \ P(H_j)}{\sum_{i=1}^{n} P(A|H_j) * \ P(H_j)} \tag{10}$$

Bayesian Networks are constructed basing on the latter expression. Every hypothesis $H_j$ out of the n possible ones is meant by the last statement. Experts provide probabilities a priori, and they are quite helpful since, generally speaking, determining the likelihood of a cause-and-effect chain of occurrences is a reasonably straightforward process.A priori probabilities are the values that provide the beginning probability for all hypotheses. The advantage of the Bayesian approach is that the a priori probability may be adjusted to reflect the facts of the process being investigated. As new information is acquired, it is then able to describe the probability of certain events.It is possible to think of the denominator of the latter formula as a normalization factor that places the probability value between 0 and 1.

A directed acyclic graph that is described as a causal network that corresponds to the variables of the process under study is the first component $G$ of a Bayesian network, which is a set $\{G, B\}$. A collection of parameters that describe the network makes up the second part of the pair $B$. Each potential combination of $x^k \in X^k$ and $par(X^k) \in Par(X^k)$ is represented by a parameter $\Theta_{\left(X^k|par(X^k)\right)} = P(X^k|par(X^k)$ in component B, where $Par(X^k)$stands for the variable's set of parents $X^k \in G$.A vertex is used to represent each variable $X^k \in G$.

Full joint probability of Bayesian Network is calculated by the next expression:

$$P_B(X^1,\ldots,X^M) = \prod_{j=1}^{M} P_B(X^j|Par(X^j)) \tag{11}$$

The Bayesian network is a mathematical model for expressing both present and absent probability relationships. When the first event is the catalyst for the second occurrence, or when there is a mechanism through which the value obtained by the first event influences the value received by the second event, the relationship is also causal.Bayesian networks are commonly depicted as graphs with some special features. A Bayesian network is made up of vertices connected by edges, much like any other graph. An edge linking the variables suggests that there is a causal connection between them. If the edge is not directed, it simply shows that there is a correlation between the variables. Undirected graphs are those that solely have undirected edges. Graphs in which all of the edges are directed are referred to as directed if the edge has an arrow pointing in the direction of dependency, or from cause to effect.

The full graph is the most likely model in the scenario of unknown structure and complete observations since it will involve the greatest number of parameters and hence provide the best fit to the data.
The Bayes formula can be written in the following form:

$$P(G|X) = \frac{P(X|G) * P(G)}{P(X)} \tag{12}$$

Where $G$is a directed acyclic graph, which stand for random variables;
$X = \{d^1,\ldots,d^M\}$–dataset.
Logarithmic form of equation (12) can be rewritten in the next way:

$$log(P(G|X)) = log(P(X|G)) + log(P(G))) - log(P(X)) \tag{13}$$

The last term $-\,log(P(X))$ in this formula serves as a penalizing element for the model's excessive complexity.Calculating $P(X) = \sum_G P(X|G)$ is a task of exponential complexity and is important to carry out correct calculations linked to model selection. To make calculations more easy, Bayesian information criterion can be applied.
It is defined in the next way:

$$log(P(G|X)) = log(P(X|G,\hat{\theta}_G)) - \frac{\log N}{2} * dim(G) \tag{14}$$

where $N-$ amount of models;
$dim(G)$–number of free parameters;
$\hat{\theta}_G$–parameter estimation of maximum likelihood;
$-\frac{\log N}{2} * dim(G)$–penalty element for models with excessive complexity.
In order to provide a thorough Bayesian analysis of loss distributions in operational risk management that uses both loss data ("backward-looking") and expert views ("forward-looking"), S. Figini et al[13] proposed an elicitation approach of previous opinions using self-assessment questionnaires.

The innovative aspect of the suggested approach is that it reduces Value at Risk (VaR) and, hence, capital charge when compared to traditional methods. In terms of capital saved by the financial institution using this strategy, this is a significant outcome. Also, the method may show to be quite helpful in estimating the operational loss distribution in situations with few losses actually seen, as earlier experiences may help to make up for the lack of data. The authors' recommended elicitation technique enables a better knowledge and communication of operational hazards, which can significantly raise awareness of risk monitoring.Moreover, the results demonstrate that specifying an informative prior using self-assessment data yields outcomes that are equivalent to those of noninformative prior models. The results can also be subjected to a sensitivity analysis using informative priors.

Bayesian networks are used by X. Hao [14] to control operational risk in a novel and efficient manner. The operational risk event tree is first created, showing how the sources of risk include internal processes including institutional factors, bank personnel factors, external variables, and system elements. The second step is the establishment of the translation mechanism from the event tree to the Bayesian network, where operational hazards of the same kind are merged into the network nodes. Lastly, a Bayesian network is used to develop the operational risk control model. With the help of the operational risk control module, four different categories of operational risk are each calculated, simplifying the process of classifying and controlling operational risks while achieving the intended control outcome.

Hybrid Dynamic Bayesian Networks (HDBNs) have been used in a novel way by M. Neil, D. Hager and L. Andersen [15] to estimate operational risk for financial organizations. They provided an explanation of a methodology for modeling financial losses due to purposeful or unintentional occurrences that may be distinguished by intricate interplay of events, their capacity to elude controls, and their propensity to eventually have progressively dire financial repercussions. By combining interactions between failure modes and controllers into a dynamic bayesian network model, authors have concentrated on modeling the causes and effects of loss occurrences.Authors shown in their work that the technique may effectively describe dependencies between events and processes in complex settings that are developing over time; we have used the financial trading process to exemplify this. In addition to providing loss distributions and VaR forecasts for two scenarios using fictional data, they gave an example model that included causative elements discovered through a rigorous examination of reported rogue trading incidents. The authors also demonstrated how their method circumvents the three main drawbacks associated with the use of Bayesian Networks technology by previous researchers: applicability, temporal dynamics, and continuous variables. They contended that Bayesian Networks provide an individual assessment of risk exposure utilizing a mix of expert knowledge, data, business environment, and internal control elements, which satisfies the Basel Accord's requirements for an advanced measurement approach (AMA).The model also has the ability to capture changes in risk exposure brought on by inadequate or effective controls. Hence, using a BN-based strategy should improve operational risk governance, provide the groundwork for solid risk management, and lower regulatory capital charges. The Bayesian Networks strategy described here stands in stark contrast to a purely statistical strategy based solely on past loss data.

Moreover, their work has introduced BN technology, algorithms, and its use in operational risk modeling. The authors demonstrated how dynamic discretization, a novel state-of-the-art method for HBNs, permits more complex modeling and analysis than is supported by earlier generations of Bayesian Networks algorithms. Also, the new method makes it very simple to model more complicated relationships between losses and severities, such as time-based losses, time to respond, time to failure, and complex mixture models.

According to M. Neil, N. Fenton and M. Tailor [16], BNs are used as a type of self-evaluation since they concentrate on determining the efficiency of the underlying business process. This would include tracking the underlying business process often (like quarterly or monthly) and using the Bayesian Network to translate these self-assessment ratings into forecasts of total loss.They have demonstrated that it is feasible to represent uncertainty regarding both the distribution of potential losses as well as the process that creates losses.Early findings from this implementation suggest that the work scales up effectively and that the Bayesian Network's formalisms satisfy the modeling requirements of business units for transparency and practicality, albeit it is too soon to declare validity or if a regulator would find the method compatible.

**2.3 Neural Networks**

The other approach, which can be used for analysis of actuarial risk is neural networks. They can be used in any context, where a set of data should be represented by a model for a specific forecast. Neural networks can be applied as a model for proposing to accept or reject a risk.

C. Dugas et. al. [17] demonstrated that main advantages of this approach in rate marketing are high degree of accuracy and performance and automatic modeling of complex feature interactions. The last asset outcomes GLM, because modeling with the last one's interaction is manually modeled and it limits an ability to detect complex relationships. Unfortunately, neural networks have one major disadvantage – lack of interpretability. They can be analyzed from input and output variables, but internal workings are not considered. GLM assign a level of significance to every feature from a set of data during the model building. But neural networks just produce a forecast without the explanation how it was obtained.

J. Lowe and L. Pryor [18] compared application of GLM and Neural Networks in pricing insurance.Both methods attempt to find a pattern in a collection of data and fundamentally operate through iteration, refining the model's "parameters" until an ideal fit is achieved. In both situations, the final product is a model that may be used to forecast future events. One of the key distinctions is that GLMs begin with a model and then assess the model's fit. Neural Networks successfully produce a model since they are primarily motivated by the training data. Compared to Neural Networks, GLMs operate with a great deal more transparency. NNs' lack of transparency has advantages and disadvantages. It has the advantage that the topology of the NN and the specifics of the transfer functions and learning techniques do not need to be specified in great detail.Although Neural Networks may potentially represent any function, GLMs are restricted to a limited number of model categories. Many real-world events are undoubtedly notably non-linear, making them less strictly suitable to modeling using GLMs. Yet, many of these events may be reduced to simpler forms and simulated using linear models from the GLM family.Neural Networks learn longer than GLMs, as the fitting algorithms are typically more generic and less sophisticated than commercially available GLM programs. GLMs, however, are likely to need more work from humans in terms of definition, programming, and subsequent analysis.

A. Gustafsson and J. Hansén [19] proposed implementation of the Combined Actuarial Neural Network (CANN), which is a combination of Neural Network and GLM.The findings demonstrated that, when compared to each of the actuarial science model evaluation tools, all CANN models outperform the GLM. As a result, it is discovered that CANN models are superior to the underlying GLM in terms of the chosen assessment techniques.

A. Azarova et al. [20] used the proposed mathematical model of investment risk estimation ,using the Hamming network, in their research in order to: eliminate errors in evaluating the investment project; account for a wide range of different primary indicators; investor requirements for profitability and payback period project; conduct a simultaneous assessment of bankruptcy; and shorten the time it takes to determine whether investing is feasible.In contrast to previous approaches, the methodological approach to investment risk estimation has been improved, allowing the use of Hamming neural networks to accurately and reasonably identify project risk and assess the viability of investing, reduce the cost of such a process, and allow specialized networks to self-learn.The Hamming neural network's mathematical framework was used to carry out the decompositional division and streamline the formalization of the structural hierarchy model of the investment risk assessment process. Additionally, it enables the evaluation of the entity's financial ratio and its suggested business project at the same time.

By utilizing a hierarchical attention recurrent network design to take advantage of the content of written documents, J. Baillargeon, L. Lamontagne, and E. Marceau [21] provided a method to enhance the standard actuarial process. Their findings demonstrate that this model performs better, is more resistant to idea shifts, and is easier to understand.Their described approach made it possible to more precisely anticipate the distribution of a counting variable and to identify risk predictors with less effort in feature engineering. These two improvements increase the scalability of our data-driven approach while preserving the highly interpretable character of feature-based models.

Prediction accuracy is just a partial representation of the majority of real-world jobs in predictive modeling, according to S. Xie [22]. The lack of completeness in a particular issue formulation necessitates the requirement for model interpretability. It is not enough to acquire greater prediction accuracy; it is also required to comprehend how the model accurately predicts. How well a model user can grasp the reasons behind the choices made during decision marking or how consistently a taught model can predict an accurate outcome are examples of non-mathematical descriptions.The purpose of the author's study was to offer some recommendations on whether sophisticated rate-making procedures are appropriate for streamlining the rate-filing review procedure. From the perspective of the insurance regulator, it is crucial to understand the rate-setting processes, the possible effects of risk variables, and the analytical mathematical model. In particular, the determination of reform and major modification of maximum coverage levels of insurance losses is made more accessible and visible to management who are responsible for a larger level of influence from regulatory policies.On the other hand, the improvement in the explainability of insurance loss data can assist stakeholders in comprehending the nature of data patterns and the connection between risk variables and the metrics used to measure loss levels, such as loss counts, loss amounts, and loss costs.The modeling issues of how claim counts, claim amounts, and average loss per claim are connected to significant risk variables in the regulation of vehicle insurance premium were taken into consideration in the author's study. In order to increase the model's explainability, artificial neural network models were applied to the issue. Variable significance measurements were also added. The collected findings from different techniques of applying weight values of Artificial Neural Networks to quantify the variable relevance were compared, and the most dominating risk factors were determined. By the investigation, the author discovered that the Garson algorithm or Olden function's variable importance measures can aid in locating the crucial factors that are involved in explaining the variance of the response variable in artificial neural network models.This research proved the value of the suggested strategies for regulating insurance rates, especially in terms of rate filing. Despite the fact that this study only examines big risks, the suggested strategy may be used to solve more general issues with insurance pricing. In order to forecast future claim losses or claim counts by pricing groups or individuals, insurance firms may employ Artificial Neural Networks models.

## III. Summary

Insurance companies are vulnerable to insolvency if the actuarial risk has not been properly calculated. In connection with the crisis phenomena that arose as a result of the aggravation of the political situation, the insurance market of Ukraine underwent significant changes.

Actuaries, who work in insurance companies, determine actuarial risk. Their task is to set insurance premiums at a rate that ensures the receipt of sufficient money. Therefore insurers can regulate any requirements and remain profitable during the current process.

Achieving realized goals requires instrumental means to minimize the growing costs of limited available resources. The need for such tools has given a reason, within the framework of methods and systems of artificial intelligence, to a whole range of information technologies designed to help in the management of society, business, the economy and the banking sphere. One of the most famous approaches is Decision Support System.

Three methods were chosen for implementation, which would be appropriate for analysis of actuarial risk. GLM is a great method for predicting future losses. It allows setting weights for features and detecting the best one for building the model, but some features can be unacceptable. Bayesian Networks can be used for estimating probability of outcome based on prior expert knowledge. But building this model is a state of art: it requires a lot of time to include all necessary variables or factors. Neural networks are a great tool, which stimulates human behavior during decision-making processes. Its only caveat is that it provides output results without explanation.

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