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NEWEST TRENDS AND TECHNOLOGIES RELATED TO ACTUARIAL MATHEMATICS - REVIEW PAPER

ANA ATANASOVA AND LIMONKA KOCEVA LAZAROVA

Abstract. This paper gives an overview of the new methods and the last trends considering actuarial mathematics. Based on a few papers that we consider relevant to our topic, we picked the information that is interesting to review. We will discuss different mathematical models and their use in the actuarial calculations for life insurance and non-life insurance.

1. Introduction

Actuarial science involves a blend of several different fields of study, from mathematics to economics, and its purpose is to provide guidelines related to making business decisions that involve risk evaluations. The math side of the actuarial science is a mix of statistics, calculus, financial mathematics, and numerical modeling.

The mathematical base of actuarial practices is applicable to life and non-life insurance. Nowadays, there are many methods with variations that are relevant to making actuarial calculations. The indicated reason that resulted in the popularity of actuarial modeling is the insertion of secure methods for practical pricing of insurance contracts. An example of that scenario would be when the insured life pays a price to the insurer, and later the insurer will pay the insured amount to the beneficiary designated by the insured person, in case an insured even happens. There are also many other actuarial models that are relevant, but in our paper we will review what researchers think about life and non-life insurance models. Our other focus will be the importance of actuarial risks over financial risks that have been considered as more important in the last few years.

2. Basic model types for actuarial calculations

Before we start to identify, report, and analyze the results that were obtained by the researchers in our chosen studies, we will first give a brief definition of what the basic model types of actuarial calculations are.

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Keywords. life insurance, non-life insurance, mathematical models, mortality tables, actuarial calculations, risk management .

One of the divisions of the actuarial calculation models is based on the moment of time in which we make use of the available data. Therefore, we can divide the models into discrete and continuous models. Continuous models allow us to use the calculations of derivatives and integrals. However, discrete approaches are more common for use. The main difference between the two is that continuous models use continuous variables to describe the likelihood of events occurring, while discrete models use discrete variables. Continuous models are more accurate but also more complex, while discrete models are simpler but may oversimplify the risk factors involved. Continuous models are typically used in insurance policies that involve a wide range of potential risks and outcomes, while discrete models are more commonly used in policies with a limited number of outcomes or risks. However, both continuous and discrete models are used in actuarial science to calculate insurance premiums and risks and are important tools for the insurance industry.

Another division is into deterministic and stochastic models. When we use stochastic models, we have two purposes and those are modeling future lifetime of the insured as a random variable and multiple-state modeling which refer to following the movement of the insured between the individual states of the system. Deterministic models are used for calculations of basic probability theory and are known as methods derived from principle of an unreal set and principle of equivalence.

Deterministic models use a fixed set of assumptions to calculate the expected outcome, and the results are based on known variables without any element of randomness. Stochastic models, on the other hand, use the probability theory and simulations to account for the inherent uncertainty in insurance policies and to estimate the range of potential outcomes. While deterministic models are easier to understand and calculate, they may not reflect the true variability and risks involved in an insurance policy.

Stochastic models provide a more comprehensive view of the risks involved, but may be more complex and time-consuming to calculate. Both models are used in actuarial science, with deterministic models being more appropriate for simpler policies, and stochastic models being more appropriate for complex policies with a wide range of possible outcomes. Ultimately, the choice between the two depends on the specific needs and requirements of the insurance policy being considered.

3. **Basic model types for actuarial calculations**

After defining the basic types for actuarial calculations, we can now make an analysis what the researchers think regarding stochastic optimal control in insurance and the risk measures that feature actuary elements. In [1] the authors described the broken-heart syndrome as a form of short-term dependence in the frames of modeling joint mortality. According to this paper, in the less economically developed countries, a stochastic mortality model of paired lives and the casual relation between their death times is more common. The effect of the death on the mortality intensity of the surviving spouse is given by a mean-reverting Ornstein–Uhlenbeck process, which captures the subsiding nature of the mortality increase characteristic of the broken-heart syndrome. The appropriate premium, considering the dependence between coupled lives through the application of the indifference pricing principle, is derived for life insurance products.

The authors in [2] are talking about the risks of selling long-term policies. According to this paper, that risk is the result of the random development of the interest rates. The paper is concentrated on the stochastic volatility models, that deals with the stochastic interest rates to obtain the risk-free price for unit-linked life insurance contracts. With the comparison of the two models, the Black-Scholes model and Heston stochastic model, it is concluded that the Hestons model is unstable comparable to the Black-Scholes. They used the Vasicek interest rate model for the short-term rate which is given with the equation

$$dr_t = k(\theta - r_t)dt + \sigma W_t^0, \;\; r_0 > 0, \;\; t \in [0, T],$$

where W_t^0 is Brownian motion represents the source of risk at moment $t = 0$, r_t is the instantaneous spot rate. The Vasicek model gives rise to Gaussian mean-reverting interest rates with long term mean equal to θ and long term variance equal to $\frac{\sigma^2}{2k}$.

Falden and Nyegaard in [3] are analyzing the retrospective reserves and bonuses within the setup of life insurance with profit. They are studying the projection of balances with and without policyholder behavior. This projection resides in a system of differential equations of the savings account and the surplus, and the policyholder behavior options of surrender and conversion to free-policy are included. In a concrete scenario, the derivation of accurate differential equations allows for an approximation method that can be used to project the savings account and the surplus, including general policyholder behavior. The results have immediate practical applications.

4. Non-life Insurance Modeling

In this chapter we will talk about non-life insurance. In order to show the point of view of some researchers, first we will give a brief overview of what non-life insurance is.

The term non-life insurance is mainly used in Europe and it gathers all insurance products that are different from life insurance. In the USA this type of insurance is known as general insurance or property insurance. This type of insurance has two main parts:

- The pricing actuary that designs and defines the price for the new insurance products

- The receiving actuary whose job is to predict the cash flows of the insurance claims.

Worth to mentioning is that usually non-life insurers face a large number of small, independent risks that can be difficult to manage individually. That is why it is important to use risk aggregation. Risk aggregation involves combining individual risks to assess the overall risk exposure of an insurer. Here we have two methods: standard and internal models. Standard models are predefined and used in the industry to aggregate risks. These models are based on historical data and use statistical methods to estimate the likelihood and severity of losses. Internal models, on the other hand, are customized models that are developed by individual insurers to reflect their unique risk profiles. Internal models are typically more complex than standard models and may incorporate additional factors such as expert judgment and qualitative information. When insurers choose between these two models there are factors that need to be considered such as: the size and complexity of their risk exposure, their risk appetite, and their resources when choosing between the two approaches [4]. It is also important for the regulators to provide clear guidelines and standards for the development and implementation of internal models, to ensure that they are consistent and transparent across the industry.
Non-life insurance pricing is the part of the actuary that runs statistical modeling and data science. Typically, in this kind of insurance, one is facing the problem of having a heterogeneous portfolio of insurance policyholders and the one that has a purpose to charge risk-adjusted prices to each of this customers. Some of the most popular models used in non-life insurance pricing and risk management are Bayesian generalized models for location, scale and shape [5, 6, 7].
Bayesian generalized models can be used to model the relationship between risk factors and claim frequency or severity, taking into account the location, scale, and shape of the distribution of the claims. The advantage of using these models is their flexibility in modeling non-linear relationships and their ability to incorporate prior knowledge and expert opinions in the modeling process.

Most of the problems that occur in statistical modeling are based on graphs and relations, but actuarial problems are dealing with ways to explain the propensity to claims. The last few years, many models are built, whose main purpose is to deal with claims, such as the hierarchical model proposed by Jonas Crevecoeur [8]. The proposed model has the potential to improve the accuracy of reserve estimates and to help insurers better manage their risk exposure. The authors in this paper gave an algorithm based on this hierarchical model for predicting the future development of claims.
The paper [9] is about the recent challenges in actuarial science; they are talking about how most of the models nowadays, that are used in actuarial pricing are based on generalized linear models (GLM). According to them with the development of

technologies, the practical experience and all the information that is easy accessible, actuaries are using predictive modeling with GLM. But, still, there are few problems that they are facing. For example, most of the explanatory variables are of categorical type and according to that the statistical analysis can face some complications such as sparsity of the underlying design matrix. Another problem that can occur is that in the regression functions, the covariates interact in a nontrivial way, which is resulting with not as good estimation.

As a relevant thing to mention here is frequency modeling. The authors are saying that the actuaries are trying to find more relevant systematic effects in the data that are usually dominated by the random part in the predictions that they want to complete.

Another relevant thing that they are talking about is that complex models are getting even more and more explored with resulting technical complications. The reason for that is that the size modeling aims to find a good compromise between model complexity and accuracy. For example, this is true within the exponential dispersion family.

As the new trends relevant in actuary is that the actuaries are using different machine learning algorithms like deep learning. They are using neural networks to deal with the data that is used in GLM. The most important thing that they are discussing are the claims in non-life insurance. According to them the claims in the non-life insurance is concerned with the predicting claims cash flows that can last over multiple years. This kind of claims they divide into 4 stages. The first stage is about algorithmic time, and in this stage actuaries are developing algorithms to predict claims cash flows. In the second stage, these algorithms are upgraded to full stochastic models. The third stage is considered as the result of the claims and the first two phases. These three stages focus on modeling aggregated claims, while the fourth stage is the advanced one when the neural networks algorithms are implemented. There are also many other researchers dealing with the GLM [10].
An important part to mention of non-life insurance is the potential for catastrophic and systemic risks. The paper [11] considers the interaction between individual insurance companies and the broader market, to assess the potential for catastrophic and systemic risk. Systemic risks are defined like the risks that affect the entire insurance market such as a financial crisis or widespread fraud [12], while catastrophic risks are defined as events that can cause significant losses to single insurer or a group of insurers, such as natural disasters or terrorist attacks.The paper suggests that regulators should focus on improving the transparency and stability of the non-life insurance market, and should consider implementing measures to reduce the concentration of the market and limit the potential for contagion and systemic risk. The paper also suggests that insurers should take steps to improve their risk management practices and increase their resilience to shocks. In [12] the dynamics of the model for the estimation of systemic risk can be conceptually divided in two

parts: one consisting of the engine for the generation of shocks coming from the real economy, and one consisting of the multi-layer contagion model that transmits and amplifies initial shocks. These two steps are implemented in a Monte Carlo simulation scheme to obtain an estimate of the probability density function of the distribution of the number of defaults and distress events. Fig.1 shows the flow chart of the contagion mechanisms.

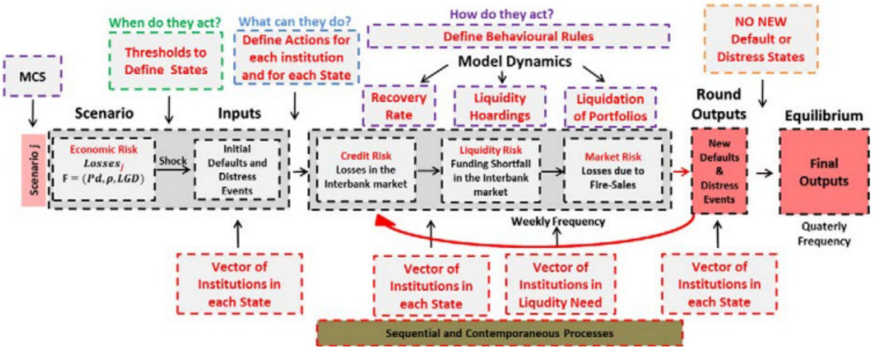

Figure 1. *Flow chart of the contagion mechanisms. The representation shows the building blocks of each simulation,* [12]

.

5. Life Insurance Modeling

After giving a brief review of what the researchers think about the non-life insurance, in this section we are going to talk about life insurance modeling. So, in order to start giving opinions, we will first see shortly what exactly life and pension insurance is.

Life insurance is very different from the non-life one. This insurance offers financial protection against unforeseen events that can occur in the next accounting year. Life and pension insurance insures life and protects against disability and death of individual policyholders over possibly their entire lifetimes. For instance, one can buy an annuity product that guarantees fixed payments over the entire remaining lifetime of the policyholder. Such a product can be bought by a single up-front premium payment at the inception of this multiple-year contract. As a consequence, life insurance is very much concerned with predicting mortality and longevity trends over several decades into the future. This prediction is typically based on time series models. Furthermore, life insurance needs to organize investments and hedging of long-term financial guarantees that are granted at inception to the policyholders. This requires good financial and economic models, as well as

suitable optimization tools for a multi-period portfolio optimization.
The authors in [9], are talking about the most static part of life and pension insurance modeling and that is the mortality forecasting. They are saying that before this few years the most popular stochastic mortality projection models were the Lee and Carter (1992) (LC) model and the Cairns et al. (2006) (CBD, for Cairns, Black and Dowd) model. Since then, the literature about stochastic mortality modeling has developed, with most of the approaches being offspring and generalizations of either the LC or the CBD model. This progress accelerated after the turn of the millennium and the subsequent financial crisis. The financial crisis has led to a low-interest-rate environment where more accurate mortality projections have gained crucial importance. In a low-interest-rate environment, miss specification of longevity trends can no longer be covered by high financial returns on investments. Moreover, national social security systems have also recently come under financial pressure, which makes the field of mortality projection a central object of interest to politicians, economists, and demographers.

Because life and pension insurance are of a long-term nature, product design is especially important to guaranteeing long term financial stability. This involves cash flow valuation, hedging of long-term financial guarantees, and minimizing lifetime ruin probabilities. There is a vastly growing literature in this field of actuarial science that is based on stochastic process modeling, optimal control, and, increasingly, on machine learning methods like neural networks or reinforcement learning. It would go too far at this stage to dive into the actuarial literature on these topics. Therefore, we only give selected interesting aspects. Clearly, it is crucial to have good stochastic models that allow us to project cash flows into the future and value these cash flows for insurance pricing, accounting, and risk management.

For cash flow valuation one typically separates mortality risk drivers from financial and economic risk drivers, more mathematically speaking, by assuming that these risk drivers can be described by independent stochastic processes. This independence assumption then allows different valuation methods to be implemented and calculated more easily. These are mostly based on the no-arbitrage principle resulting in the consideration of martingales for price processes.
Relevant work in this field of research has been done in [13, 14]. In [13] the authors have derived a partial differential equation for fair pricing of equity-linked life insurance contracts in a general financial-actuarial market with stochastic interest rate, equity, volatility and mortality. The paper develop a stable computational algorithm for fair pricing of insurance liabilities in incomplete markets which can be used for a wide variety of financial and insurance products.
The authors in [14] introduced a novel hybrid valuation operator based on a decomposition of the product's payoff in a financial, hedgeable part, a diversifiable

part and a neither hedgeable nor diversifiable part.
Insurance companies make extensive use of Monte Carlo simulations in their capital and solvency models. To overcome the computational problems associated with Monte Carlo simulations, most large life insurance companies use proxy models such as replicating portfolios . The author in [15] proposed a model in which used neural networks are used as a proxy model. It shown how to apply risk-neutral pricing on a neural network to integrate such a model into a market risk framework. Similar works are done in [16, 17]. In [17] the author has shown that the neural networks used data more efficiently than nested Monte Carlo method. The author showed that when a fixed "simulation budget" is given, neural networks deliver more accurate results than using that budget for nested Monte Carlo (Fig.2). In the paper it is shown that neural networks improve proxy modelling for risk management in life insurance.

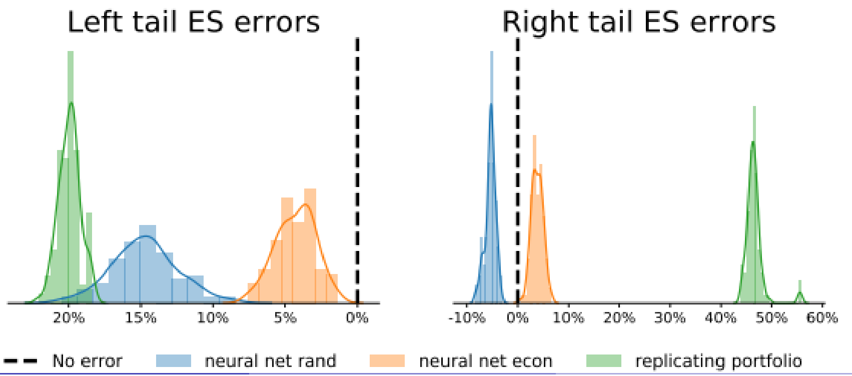

FIGURE 2. *Results of quality comparison Neural networks vs. Monte Carlo,* [17]

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In [18], the authors have implemented the hitherto most promising model in proxy modeling consisting of ensembles of feed-forward neural networks and compared the results with the least squares Monte Carlo (LSMC) polynomial regression. They showed that flexibility and accuracy of neural network models open the door to a variety of further applications, ranging from asset-liability management to product management.
Similarly, the authors in [19] trained the neural network model using the data from 1999 to 2017 and provided strong results of forecasting using Artificial Neural Network Models. In [20] the author introduced a framework for individual claims forecasting that it can be utilized in loss reserving. By leveraging Bayesian neural

networks and stochastic output layers, that approach provides ways to learnuncertainty from the data. The author showed that the approach is able to produce cash flow estimates for multiple future time periods.

In life insurance the calculation and projection of the mathematical reserve are very important. The authors in [21] proposed a new approach for individual claims reserving and they showed how individual development factors can be modelled as the prediction target of a system of Bayesian neural networks. Similarly, in [22] the authors have presented a claims reserving technique that uses claim-specific feature and past payment information in order to estimate claims reserves for individual reported claims. They designed one single neural network allowing us to estimate expected future cash flows for every individual reported claim.

These valuation methods play a crucial role in solvency assessments, long-term investment considerations, and naturally, in product design. Related to the latter, we focus on one particular idea that has recently gained some popularity. In view of increasing mortality improvements, low interest-rate environments, and increasing regulatory constraints, private life insurance companies are more and more reluctant to offer long-term longevity and financial guarantees to customers.

Therefore, in the actuarial literature, the old idea of the so-called tontine has returned. The first tontine system was developed in 1653 by the Italian Lorenzo de Tonti, and tontines gained much popularity between the seventeenth and nineteenth century, especially in France and the United Kingdom. In those times, tontines were used as investment plans to raise capital. A tontine is a financial scheme that is organized by either a government or a corporation. Everyone can subscribe to a tontine scheme by paying an amount of capital into the tontine. This investment then entitles the subscriber to receive an annual interest until he/she dies. When a subscriber of the tontine scheme passes away, his/her share is reallocated among the survivors of this subscriber. This process terminates as soon as the last subscriber has died. Thus, the tontine essentially is a self-organizing pension system that does not involve an insurance company, and it also does not involve any longevity guarantees. It only needs a body that organizes the scheme and that manages the capital of the subscribers. In contrast to private (personal) investments, family members will not inherit tontine shares in case of death of the tontine subscriber, but these shares go instead to the survivors in the tontine scheme.

6. Conclusion

Life and non-life insurance are two broad categories of insurance products that cover different types of risks. Life insurance provides financial protection to individuals and their families in the event of death or disability, while non-life insurance (also known as property and casualty insurance) covers damage to property or liability for injuries and other losses.

In recent years, new technologies have emerged that are transforming both the life and non-life insurance industries. In life insurance, for example, insurers are using data analytics and machine learning algorithms to better assess risk and offer personalized policies. Wearable devices and health tracking apps are also being used to monitor policyholders' health and encourage healthy habits, which can help reduce claims and premiums.

In non-life insurance, new technologies such as telematics and the Internet of Things (IoT) are being used to monitor risks and provide more accurate pricing for policies. For example, car insurance companies are using telematics devices to track drivers' behavior and offer personalized policies based on their driving habits. Similarly, smart home devices and sensors are being used to monitor risks such as water leaks, fires, and theft, and offer customized policies based on the risk profile of each home.

Another area of innovation in both life and non-life insurance is blockchain technology, which can improve transparency, security, and efficiency in insurance transactions. Blockchain can also enable new types of insurance products, such as peer-to-peer insurance, which allows individuals to pool their risks and share the costs of claims.

Overall, new technologies are transforming the insurance industry, offering new opportunities for insurers to better assess and manage risk, offer more personalized policies, and improving customer experience. However, these technologies also raise new challenges, such as data privacy and security concerns, and the need for insurers to adapt to changing customer expectations and preferences.

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