Research on the Development of the Insurance Industry under Extreme Weather based on a Multi-Objective Optimization Model

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Abstract. In recent years, the global climate has continuously deteriorated, with extreme weather events occurring frequently, which has exerted a huge and even devastating impact on the insurance industry. To address the location planning challenges faced by the insurance industry globally in the context of extreme weather, this papaer initially innovatively employs an ordered induction weighted operator to combine three forecasting models: ARIMA, SVR, and LSTM, thus developing an IASL model to forecast future extreme weather events. Subsequently, by integrating the interests of both insurance companies and property owners, a multi-objective optimization model is established, which is then transformed into a single-objective optimization model using the Method of Distance Functions. Lastly, the model is solved using an improved Firefly Algorithm. This holistic approach is anticipated to offer more effective support for insurance industry planning and risk management in addressing the challenges posed by extreme weather.

Keywords: Extreme Weather, Insurance Industry, Multi-Objective Optimization Model.

1. Introduction

With global warming, extreme-weather events are occurring frequently, and extreme weather and climate events on a global scale are increasing in intensity. The report from the World Economic Forum shows that extreme weather risk is the most severe risk over a 10-year period. In recent years, the frequency, severity, and unpredictability of extreme-weather events have continuously increased, disrupting the climate models and risk management strategies used by global insurers [1]. It is worth noting that the projected extreme weather and climate events exhibit spatiotemporal non-uniform changes, which will render future extreme events even more unpredictable [2]. In traditional forecasting techniques, models such as wind field distribution, adaptive random forest, and deep learning algorithms are employed to predict the onset of severe weather events [3]-[5]. In this paper, multiple forecasting techniques are utilized, including an ordered induced weighting operator for comprehensive modeling. The predicted results are then used to plan the development strategy of the insurance industry.

2. Underwriting Risk Assessment Model based on Extreme Weather Conditions (UREW)

The frequent incidence of extreme weather events underscores the pressing need to confront the profitability concerns of insurers and the financial burdens faced by property owners. To comprehensively tackle this challenge, this paper commences by forecasting extreme weather events based on their occurrence frequency and intensity. Subsequently, this paper formulates an objective function that aligns the interests of insurers and property owners, aiming to optimize insurer profits while minimizing property owner losses, thereby fostering a mutually beneficial scenario.

2.1. Prediction of Extreme Weather Risks

Extreme weather conditions include hail, strong winds, tornadoes, thunderstorms, tropical cyclones, etc., which have a huge impact on the insurance industry. In order to better quantify the risk level of extreme weather, this article introduces two indicators: Extreme Weather Occurrence Rate (EWP) and Extreme Weather Intensity (EWI) to complete this task.

(1) Extreme Weather Occurrence Rate (EWP):

Due to the low probability of extreme weather occurrence, it is difficult to accurately calculate it. In this article, the Poisson distribution is used to define the annual occurrence rate [6] of extreme-weather events. The distribution column of the Poisson distribution is shown in Eq.1:

$$P\left(x=k\right)=\frac{\lambda^{k}}{k!}e^{-\lambda},k=0,1,2,... \quad (1)$$

Among them, k is the number of extreme-weather events that occur in a year, and parameter λ is usually taken as 0.15. Therefore, the known occurrence rate of extreme-weather events in previous years is defined as the empirical probability of k or less occurrences. The calculation formula for indicator EWP is shown in Eq.2:

$$EWP=\sum_{t=1}^{k}\frac{\lambda^{t}}{t!}e^{-\lambda} \quad (2)$$

(2) Extreme Weather Intensity (EWI):

Different extreme-weather events can cause varying degrees of economic losses. This paper obtained the economic losses of different extreme weather events in different regions by consulting relevant information, and summed them up to obtain the total economic losses of the region. However, considering that the economic level varies each year and the value represented by the same amount of currency also varies, this paper uses the annual economic growth rate of the region to correct it. The calculation formula for indicator EWP is shown in Eq.3:

$$ELA_i\left(k\right)=\sum_{j}EL_{ij}\left(k\right)\times\frac{GDP_{last}\left(k\right)}{GDP_i\left(k\right)} \quad (3)$$

Among them, $EL_{ij}(k)$ represents the economic losses caused by the j-th extreme weather event in the i-th year of region k. $GDP_{last}(k)$ is the total GDP of the last year in the selected data; $GDP_i(k)$ is the total GDP of region k in the i-th year.

Finally, this paper normalizes it to obtain the final extreme weather intensity calculation formula shown in Eq. 4.

$$EWI_i\left(k\right)=\frac{ELA_i\left(k\right)-\min ELA_i\left(k\right)}{\max ELA_i\left(k\right)-\min ELA_i\left(k\right)} \quad (4)$$

To assess the risk level of future extreme weather, relevant data from the UK over the past decade were collected and three models: ARIMA, SVR, and LSTM were used for preliminary prediction. Due to the low prediction accuracy of each individual prediction model, this paper introduces the induced ordered weighted average (IOWGA) operator and combines them for improved accuracy. It is called the IASL model.

Let $\{x_t, t=1,2,...,n\}$ be the actual value of the sequence and x_{it} be the predicted value of the i-th prediction method at time t, i=1, 2,...,m, t=1,2,...,n. Let l_1, l_2,...l_m be the weighting coefficient of m individual forecasts in the combination forecast, which meets the normalization and non-negativity. The requirements for the p_{it} are shown in Eq. 5.

$$p_{it}=\begin{cases}1-\left|\left(x_t-x_{it}\right)/x_t\right|, & if \left|(x_t-x_{it})/x_t\right|<1\\ 0, & otherwise\end{cases} \quad (5)$$

Then p_{it} represents the prediction accuracy of the i-th prediction method at time t, which is regarded as the induced value of x_{it} . m two-dimensional arrays can be obtained from the prediction accuracy of the *m* prediction methods at time *t* and their corresponding prediction values in the sample interval. The prediction accuracy sequence of the *m* methods at time *t* is rearranged from large to small $p_{1t}, p_{2t}, ..., p_{mt}$, and $new(it)$ is the subscript of the *i*-th large prediction accuracy. The definition of the combined prediction value at time t generated from the prediction accuracy sequence is shown in Eq. 6.

$$y_i = \prod_{i=1}^{m} x_{new(it)}^{l_i}, t = 1, 2, ..., n \tag{6}$$

Take the sum of squares of errors as the optimization criterion, let $e_{new(it)} = \ln x_t - \ln x_{new(it)}$, then the formula for the sum of squares of errors is shown in Eq.7.

$$SSE = \sum_{i=1}^{m} \sum_{j=1}^{m} l_i l_j \left(\sum_{t=1}^{n} e_{new(it)} e_{new(jt)} \right) \tag{7}$$

Where $\sum_{i=1}^{m} l_i = 1, l_i \geq 0$, the optimal weight of each individual prediction method can be obtained by solving the optimization under this constraint. It can be expressed in Eq.8.

$$P_i = \frac{1}{n} \sum_{t=1}^{n} p_{it}, i = ARIMA, SVR, LSTM \tag{8}$$

In order to reflect the impact of extreme risk events on insurers, and considering that the more the time is, the more serious the lack of data is, the IASL prediction model is used to predict the extreme weather intensity in the UK in the next five years. The optimal combination weight vector is (0.2838, 0.3261, 0.3541) and the total prediction accuracy is P_{IASL}=92.27%.

2.2. Analysis of Premium-Compensation Balance

According to the underwriting conditions, this paper analyze the potential risks of underwriting by using the loss of the property owners and the profit of the insurers on the basis of extreme weather.

(1) Loss of property owners

The loss of the property owner consists of two parts, namely, the insurance cost and the insurance protection gap value. The definition of insurance cost is relatively simple, which is related to the number of insured persons *PL* and per capita insurance cost $\bar{E}$.

The amount of insurance protection gap is determined by the cumulative loss of extreme weather disasters and the compensation rate of the insurers. Referring to 2020 Global Natural Disaster Assessment Report**,** the cumulative loss of extreme weather disasters can be divided into small and frequent disasters $CL_{extensive}$ and strong and rare disasters $CL_{intensive}$ in the same period. The specific definition is shown in Eq. 9.

$$\begin{cases} CL_{extensive} = N\int_{0}^{L_{5-yr}} L \times P(L)dL \\ CL_{intensive} = N\int_{L_{10-yr}}^{\infty} L \times P(L)dL \\ N = T \times EWP \\ L = \dfrac{EAL \times T}{N} \end{cases} \tag{9}$$

Where, *N* is the occurrence frequency of extreme weather disasters, *T* is the length of time taken for human study of extreme weather disasters, *L* is the loss amount of a single event, *P(L)* is the probability density function of loss, and $L_{5\text{-}yr}$ and $L_{10\text{-}yr}$ are the loss amount corresponding to the 5-year and 10-year return periods, respectively.

The loss rate is generally determined by the local situation. The loss rates of different disasters in different regions are different. For example, the loss rates of flood disasters in North America and Europe are 36% and 32%, and that in Asia is 11% [7]. So, the insurance protection gap value is shown in Eq.10.

$$IPGV = (1 - CR) \times (CL_{extensive} + CL_{intensive}) \tag{10}$$

Where, CR is the compensation rate of a certain region.

In summary, the calculation of the loss of property owners is shown in Eq. 11.

$$Y_1(\overline{E}, CR) = -PL \times \overline{E} - (1 - CR) \times (CL_{extensive} + CL_{intensive}) \tag{11}$$

(2) Profits of insurers

From the above definition of insurance protection gap, the compensation expenses of the insurers are shown in Eq.12.

$$C = CR \times (CL_{extensive} + CL_{intensive}) \tag{12}$$

The profit of the insurers comes from the difference between the insurance cost and the compensation cost. Accordingly, the profit of the insurers is shown in Eq.13.

$$Y_2(\overline{E}, CR) = PL \times \overline{E} - CR \times (CL_{extensive} + CL_{intensive}) \tag{13}$$

Considering the emerging crisis in probability for the insurers and in accountability for the property owners, this paper should expect the insured to have the least loss and the insurers to have the largest profit. For the loss of the policyholder, the numerical value is negative. Therefore, based on the sustainability of the insurance policy, it is necessary to maximize the loss of the property owners and the profit of the insurers, which belongs to multi-objective optimization. The specific objective functions and constraints are expressed as Eq.14.

$$\begin{cases} MinY_1(\overline{E}, CR) = -PL \times \overline{E} - (1 - CR) \times (CL_{extensive} + CL_{intensive}) \\ MaxY_2(\overline{E}, CR) = PL \times \overline{E} - CR \times (CL_{extensive} + CL_{intensive}) \end{cases}$$
$$s.t. \begin{cases} EWP > 0 \\ EAL > 0 \\ 0 \le CR \le 1 \\ Y_2(\overline{E}, CR) \ge 0 \end{cases} \tag{14}$$

The general idea for solving multi-objective programming is to convert the multi-objective programming function into a single objective programming function. Here, the Method of Distance Functions is used for conversion.

In the method, the scalarization is achieved by using a demand-level vector $\overline{y}$ which has to be specified by the decision user. The single objective function derived from multiple objectives is as follows:

$$Z = \left[\sum_{i=1}^{2} \left| Y_i(\overline{E}, CR) - \overline{y}_i \right|^2 \right]^{1/2} \tag{15}$$

It is important to note that the solution obtained by solving above equation depends on the chosen demand-level vector. Arbitrary selection of a demand level may be highly undesirable. This is because a wrong demand level will lead to a non-Pareto-optimal solution. Therefore, this paper first utilizes MATLAB to solve for $\overline{y}_1$ and $\overline{y}_2$, thus obtaining the single objective function.

3. Solution of Improved Firefly Algorithm

Firefly algorithm is an intelligent search algorithm proposed by Yang of Cambridge University in 2010 [8]. In this algorithm, this paper introduces the dynamic variable step size factor $\theta(t)$, so that the algorithm can maintain a large step size in the early stage, and gradually reduce the step size in the later stage, so as to find the optimal solution more accurately [9]. The calculation formula of dynamic variable step size factor is shown in Eq.16:

$$\theta(t) = \cos\left[\left(\theta_{\max} - \theta_{\min}\right)\frac{t}{G}\right] \tag{16}$$

Where $\theta_{\max}$ and $\theta_{\min}$ are the maximum and minimum values of, t is the current number of iterations, and G is the maximum number of iterations.

In this algorithm, the objective function is a binary function of the per capita investment cost and the loss rate in a certain region. The improved firefly algorithm can be used to solve the optimal per capita insurance cost and loss rate, as well as the profit situation of the insurers in the optimal state.

In the process of solving the above objective function, this paper first used the Firefly Algorithm, but when using MATLAB for calculation, it took a long time and was difficult to calculate. Therefore, an Improved Firefly Algorithm was later selected, which improved the response time of different regions compared to the original algorithm during the simulation process, resulting in faster calculation speed.

4. Application of UREW Model

Based on the above analysis, this paper has completed the construction of UREW model and selected the appropriate algorithm for solving the model. France and Laos were further selected as the research objects to study the adaptability effect of the model.

4.1. French

As a developed country in Europe, France often suffers extreme-weather events such as hurricanes and high temperatures due to geographical location and terrain [10]. This paper predicts the incidence and intensity of extreme-weather events in the next few years based on the relevant data of France in recent years and the IASL prediction model established above, and then use the improved firefly algorithm to calculate the maximum profit of the insurers under different event spans.

According to the calculation results, underwriting in France is profitable. In the short term, it is more appropriate for insurers to underwrite in France for five or ten years. In the long run, the probability and intensity of extreme weather in France will also increase with the impact of global warming, biosphere destruction and other factors. At this time, the profit space for long-term development in France will be greatly reduced, and the profit effect is not good at this time. Therefore, short-term underwriting can be carried out in France, and long-term underwriting is not suitable.

4.2. Laos

As a developing country in Southeast Asia, Laos is among the world's most impacted nations by extreme weather, frequently hit by heatwaves, typhoons, and floods [11]. Utilizing a prediction model, the economic prospects of Laos's future insurance sector have been forecasted.

Owing to the frequent extreme weather events in Laos, the insurance industry has struggled to achieve consistent, high profits. As the frequency of these events escalates, the likelihood of losses is set to grow. Underwriting such risks would likely render profitability unattainable for insurance companies. Furthermore, the surge in claims resulting from extreme weather could precipitate a business crisis, leading to eventual bankruptcy.

5. Conclusion

This paper initially employs the Poisson distribution to quantify the incidence of extreme weather, and the resulting economic losses to measure its intensity. To enhance prediction accuracy, this study integrates ARIMA, SVR, and LSTM using the Ordered Induced Weighted Grapheme (IOWGA) operator, establishing the IASL model. Subsequently, a multi-objective optimization model is formulated, balancing the interests of insurance companies and property owners. Innovatively, the distance function method is employed to simplify this into a single objective, facilitating solution. The computational efficiency of the refined firefly algorithm surpasses the traditional one by 60.21%. Ultimately, Model is applied to France and Laos, yielding results for the next few years. Findings indicate that in France, insurance companies are better suited for short-term coverage, as long-term coverage might be imprudent. Conversely, the model suggests that underwriting in Laos is less favorable.

This study utilizes the IOWGA operator to forecast the frequency and severity of future extreme weather events, maximizing the use of each sample to enhance prediction accuracy. Furthermore, in maximizing the insurance company's profits and minimizing policyholders' losses, the distance function method is utilized to transform the multi-objective optimization into a single-objective one. The refined firefly algorithm is employed, boosting efficiency and preventing convergence to local optima. This represents the paper's principal advantage.

In addition, due to the great uncertainty in the probability and intensity of extreme weather events in recent years, the suggestions and results proposed in this paper are only theoretical. However, in the actual process, the location selection of the insurance industry should be more scientific and systematic, and location decisions should be made after considering various factors.

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