Chapter 2.

APPLICATION OF ARTIFICIAL INTELLIGENCE IN PROJECTING CLAIMS WITHIN NON-LIFE INSURANCE

Projection of expected claims represents one of the most important traditional roles of actuaries in charge of estimating claims reserves in non-life insurance. Deterministic and stochastic methods are commonly used to determine claims reserves; however, the fact that the projection of claims is based on incomplete data from the past led to the application of machine learning techniques.

In this chapter of the monograph, we will first define claims reserves as well as the statistical basis for their calculation. The focus of the methodological part of the chapter will be on the most important claims reserving methods: chain-ladder (CL), including the Mack version of the model, Bornhuetter-Ferguson (BF), Cape Cod (CC), and Generalised Linear Models (GLM).

Starting from the hypothesis that applying artificial intelligence can contribute to increased efficiency and innovation in non-life insurance claims reserving, the last section of the chapter will present the results of testing Machine-led Reserving (MLR) algorithms in selecting the most accurate claims prediction method.[61]

1. CLAIMS RESERVES - DEFINITION AND STATISTICAL BASIS FOR THEIR CALCULATION

The term claims reserves refers to the estimated value of claims due to an accident that has occurred before the end of the accounting period and which insurance companies are obligated to pay based on the insurance contract. During the period from when a claim is made until it is fully estimated and settled, reserves are established for Reported But Not Settled (RBNS) claims.

These reserves also account for losses from reactivated claims, which are claims that were previously settled but have since been reopened due to additional compensation requests made to the insurance company. Due to the time difference between the date of the accident and making a claim to the insurer, Incurred But Not Reported Reserves (IBNR) are estimated. Typically, claims reserves constitute a significant portion of the total technical reserves in non-life insurance.

[61] *The insights and findings from the research conducted by Willis Towers Watson, kindly provided by MSc Miona Graorac, Senior Consultant, were used in the preparation of this chapter.*

Determining the size of the reserves is the result of an in-depth business analysis of the insurer, based on using generally accepted actuarial methods.[62]

Traditional methods of projecting claims reserves are based on the data on the number of reported claims, or the amount of settled, reserved, or incurred (the total number of reported) claims which are classified according to the period of occurrence of the accident and the period of reporting, settlement, or reservation. In this chapter of the monograph, we will discuss the claim reserving method based on the triangles of cumulatively settled or reported (incurred) claims, grouped according to the period of occurrence of an accident (year, quarter, or month).

Figure 1 depicts the loss triangle of cumulatively settled or reported (incurred) claims, which comprises the statistical data from the loss triangle of incrementally settled or reported (incurred) claims, i.e. settled or reported claims in a certain development period. It is important to emphasise that the diagonal data of the group represent the development of claims during the same calendar period.

Figure 1. Run-off triangle of cumulatively settled or reported claims

Period of Occurrence	**Development Period**								
	1	**2**	**...**	**j**	**...**	**n+1-i**	**...**	**n-1**	**n**
1	C_{11}	C_{12}	...	C_{1j}	...	$C_{1,n+1-i}$		$C_{1,n-1}$	$\mathbf{C_{1,n}}$
2	C_{21}	C_{22}	...	C_{2j}	...	$C_{2,n+1-2}$		$\mathbf{C_{2,n-1}}$	$\hat{C}_{2,n}$
...	...	...	...	...	...	...	...	...	...
i	C_{i1}	C_{i2}	...	C_{ij}	...	$\mathbf{C_{i,n+1-i}}$	...	$\hat{C}_{i,n-1}$	$\hat{C}_{i,n}$
...	...	...	...	...	...	...	...	...	...
n+1-j	$C_{n+1-j,1}$	$C_{n+1-j,2}$	...	$\mathbf{C_{n+1-j,j}}$	...	$\hat{C}_{n+1-j,n+1-i}$	...	$\hat{C}_{n+1-j,n-1}$	$\hat{C}_{n+1-j,n}$
...	...	...	...	...	...	...	...	...	...
n-1	$C_{n-1,1}$	$\mathbf{C_{n-1,2}}$	...	$\hat{C}_{n-1,j}$	...	$\hat{C}_{n-1,n+1-i}$	...	$\hat{C}_{n-1,n-1}$	$\hat{C}_{n-1,n}$
n	$\mathbf{C_{n,1}}$	$\hat{C}_{n,2}$	...	$\hat{C}_{n,j}$	...	$\hat{C}_{n,n+1-i}$	...	$\hat{C}_{n,n-1}$	$\hat{C}_{n,n}$

Source: Adapted from Wüthrich, M.V., & Merz, M. (2008). Stochastic Claims Reserving Methods in Insurance. Vol. 435. Chichester: John Wiley & Sons.

The value of claims reserves is obtained by applying the appropriate methodology from the projected values of cumulatively settled or reported claims, displayed in the lower triangle, along with using the data from the upper triangle (shaded area) whith the historical data on cumulatively settled or reported claims in a certain

[62] *Kočović, J., & Mitrašević, M. (2010). Uloga i značaj aktuara za uređenje tržišta osiguranja, Ekonomska politika i razvoj, Belgrade: Faculty of Economics, University of Belgrade, pp. 127-146.*

development period, grouped according to the period of occurrence (Figure 1)[63]. Based on the estimated final losses in the period of occurrence *i* ($\hat{C}_{i,n}$) displayed in the last column of Figure 1, claims reserves for the accident year *i* will amount to[64]:

$$\hat{R}_i = \hat{C}_{i,n} - C_{i,j}\,, \tag{1}$$

where:

$\hat{R}_i$ - the evaluation of total reserves for claims incurred in the year *i* if the evaluation is based on the loss triangle of settled claims, or the reserves for unreported claims if the evaluation is based on the loss triangle of reported (incurred) claims,

$C_{i,j}$ - cumulative claims originating from the period of occurrence *i*, settled (reported) by the end of the period *j* (i=1,...,n;j=n-i+1) and on the previous scheme (Figure 1) they are shown on the last diagonal of the shaded triangle. It follows that:

$$C_{i,j} = \sum_{h=1}^{j} Y_{i,h}\,, \tag{2}$$

where $Y_{i,h}$ denotes the claims incurred in the year *i* and settled (reported) in the year *h*.

Total claims reserves can also be defined as the sum of all projected future (incremental) claims[65]:

$$\hat{R} = \sum_{i=2}^{n} \sum_{j=n-i+2}^{n} Y_{i,j}\,, \tag{3}$$

Actuaries can use deterministic and stochastic methods to calculate the final amount of claims and reserves, and with new achievements in computer data processing it is enabled to apply the algorithms based on machine learning.

[63] *Peremans, K., Van Aelst, S., & Verdonck, T. (2018). A Robust General Multivariate Chain Ladder Method. Risks 6, no. 4: 108. doi:10.3390/risks6040108.*

[64] *Kočović J., & Mitrašević M., & Trifunović D. (2017). Advantages And Disadvantages of Methods for Assessment of Loss Reservations in Non-life Insurance, U: XLIV Simpozijum o operacionim istraživanjima SYM-OP-IS 2017, Zlatibor 25th-28th September, 2017, Belgrade: Department School of Civil Engineering and Geodesy of Applied Studies, pp. 507-512.*

[65] *Chang, L., Gao, G., & Shi, Y. (2024). Claims Reserving with a Robust Generalised Additive Model. North American Actuarial Journal, pp. 1–21. https://doi.org/10.1080/10920277.2023.2259445.*

2. METHODOLOGICAL ASPECT OF CLAIMS ESTIMATION IN ACTUARIAL THEORY AND PRACTICE

As it was underlined in the introductory part, in the methodological part of this chapter the focus is on chain-ladder methods, Mack chain-ladder method which by calculating the variances of observations enhances the traditional chain-ladder method, Bornhuetter-Ferguson, Cape Cod, and Generalised linear models. Apart from them we will briefly explain the expected loss ratio method since it can represent the basis for the Bornhuetter-Ferguson method. These methods, which are analysed in majority of papers in the field of actuarial science, and some of the research and the results are presented in the chapter. Nevertheless, despite numerous theoretical analyses dedicated to the methods, research initiated in the last quarter of 2015 by the International Actuarial Association under the research field Actuarial Studies in Non-life Insurance (ASTIN), aimed at examining companies' experiences with claims reserves, demonstrated that commonly accepted methods in actuarial theory are not equally present in practice. The research covered 535 insurance companies from 42 countries whose realised premiums account for 87% in the non-life insurance premium globally. The results of the research[66] indicate that chain-ladder and Bornhuetter-Ferguson are most frequently used deterministic methods. Since 57.6% of the global non-life insurance premiums are generated in the United States of America[67], we will highlight the experiences of US-based insurance companies that have been covered by research. The data illustrate that all companies in the US use chain-ladder and Bornhuetter-Ferguson as the main claims reserving methods, while 83% of them also use expected loss ratio method as the main method, and 17% as a peer method. Even though we have described the Cape Cod method in this chapter based on the research performed by the software consultant company Willis Towers Watson (WTW), practice has shown that less than 40% of the insurance companies covered by the research use this method, with majority of them using it as a peer method, while only about 10% use it as the main method. Half of the insurance companies in the USA do not use the Cape Cod loss reserving method.

As for stochastic reserving methods, the most widely used one is the Mack chain-ladder. ASTIN data published in 2016 pinpoint that over 45% of insurance companies use this method, in particular, approximately 30% of them use it as the main one. Similar to Cape Cod, GLM as a stochastic method frequently used in theoretical research is not extensively applied in the practice of the insurance companies which have been included in the research.

---

[66] *ASTIN working party on non-life reserving practices. (2016). Report: Non-life Reserving Practices. Available at: https://www.actuaries.org/astin/documents/astin_wp_nl_reserving_report1.0_2016-06-15.pdf.*

[67] *Swiss Re Institute. (2023). World Insurance: Stirred, and not Shaken. Sigma No 3/2023, Available at: https://www.swissre.com/institute/research/sigma-research/sigma-2023-03.html.*

Deterministic methods imply that the projection of ultimate claims is calculated based on past experiences and assume that the loss development pattern manifested in the past will continue in the future, therefore these methods are recommended when more complex ones would not lead to better calculation results. One of the oldest methods, and as the previous findings indicate the most commonly used one for estimating claims reserves, which in the evaluation of ultimate claims starts from the aforementioned loss development triangle, is the chain-ladder method, described in Mack (1993)[68].

Chain-ladder method

The estimation of the final cumulative amount of losses incurred in the period *i* according to the chain-ladder method can be shown in the following way:

$$\hat{C}_{i,n} = C_{i,j} \cdot \hat{f}_j \cdot \ldots \cdot \hat{f}_{n-1}, \tag{4}$$

where:

$\hat{f}_j$ - the estimated value of loss development factor on the basis of the data on cumulatively settled (reported) claims organised in accordance with Figure 1, as a weighted average of individual development factors $\left(\hat{f}_{i,j} = C_{i,j+1} / C_{i,j}\right)$:

$$\hat{f}_j = \frac{\sum_{i=1}^{n-j} C_{i,j+1}}{\sum_{i=1}^{n-j} C_{i,j}}. \tag{5}$$

The tail factor can be applied to assess possible further loss development after the latest development factor.[69]

When applying this method, one should bear in mind that the assumptions regarding the equality of individual development factors in a certain development period for all periods of occurrence of accidents and the mutual independence of the number of settled claims for all accident years, on which the chain-ladder method is based, are mostly not met in practice. In order to improve the reserving results, the chain-

[68] *Mack, T. (1993). Distribution-free Calculation of the Standard Error of Chain-ladder Reserve Estimates. ASTIN Bulletin, 23/2, pp. 213-225.*

[69] *More information about the functions that can be used to estimate tail factors: Mitrašević, M. (2015). Practical Aspects of Harmonisation of Regulations Related to Calculation of Technical Reserves Held by Non-life Insurers, Strategic Management, Vol. 20, No. 3, pp. 044-051; Kočović, J., & Koprivica, M. (2021). Ocena repnog faktora razvoja šteta ekstrapolacijom teorijskog oblika krive. SYM-OP-IS 2021, Urošević, D., Dražić, M., Stanimirović, Z. (eds.), Belgrade: Faculty of Mathematics, University of Belgrade, pp. 123-128.*

ladder method should be applied cautiously, being aware of all its shortcomings accompanied by alternative, more complex reserving methods, and actuaries' subjective judgment based on their experience and expertise.[70]

Bornhuetter-Ferguson (BF) method

In their work published in 1972, Bornhuetter and Ferguson presented the method for estimating reserves for unreported claims that combines the loss ratio method and the incurred loss development method by accident years.[71] Final numer of claims for the accident year *i* according to the Bornhuetter and Ferguson method are estimated in the following way[72]:

$$\hat{C}_{i,n}^{BF} = C_{i,j} + \left(1 - \frac{1}{F_j}\right) \cdot \hat{C}_{i,n}, \quad (6)$$

where:

F_j -cumulative loss development factor for the period of occurrence *i*, from the development period *i* to the final one (*i*=1,...,*n;j*=*n*-*i*+1): $F_j = \hat{f}_j \cdot ... \cdot \hat{f}_{n-1}$,

$\hat{C}_{i,n}$ -assessment of the final cumulative amount of the loss incurred in the period *i*.

The estimate of the expected final losses originating from the period of occurrence *i* can be derived by multiplying the earned premium for that period with the expected loss ratio, as shown in the following formula (7). The final cumulative losses for the period of occurrence *i* according to the method of the expected loss ratio are evaluated as follows[73]:

$$\hat{C}_{i,n}^{LR} = E(s)_i \cdot \tilde{P}_i, \quad (7)$$

where:

$\tilde{P}_i$ - the earned premium in the period *i*,

$E(s)_i$ - predefined loss ratio in the period *i* (the ratio of ultimate claim losses and the total written premium).

[70] *Kočović, J., Mitrašević, M., Jovović, M. (2014). Methodological Basis and Practical Issues of the Chain-ladder Method, Актуарий-информационно-аналитический бюллетенъ-No1(5)-14, pp. 40-44.*

[71] *Bornhuetter, R. L., and Ferguson, R. E. (1972). The Actuary and IBNR, Proceedings of the Casualty Actuarial Society 59, pp. 181—195.*

[72] *Kočović, J., Trifunovic, D., Mitrašević, M. (2019). Advantages And Disadvantages Of Methods For Assessment Of Loss Reservations In Non-Life Insurance. Yugoslav Journal of Operations Research, 29(4), pp.553-561.*

[73] *Jovović, M. (2015). Merenje rizika pri utvrđivanju solventnosti neživotnih osiguravača. doctoral dissertation, Belgrade: Faculty of Economics, the University of Belgrade.*

This technique has proven to be the appropriate one for the types of insurance where claims are reported long after the policy expires and where there is a significant variance in the proportion of the claims reported in earlier development years; consequently, the method such as the chain-ladder method can lead to unsatisfactory results[74].

Stanard-Bühlmann method

Similar to the previous method, with the Stanard-Bühlmann method an attempt was made to overcome the shortcomings of the chain-ladder method and obtain more precise interpretations of developmental factors. The method independently developed by Jim Stanard and Hans Bühlmann is often called the Cape Cod method[75], and its usage was explained by Straub in the book published in 1988.[76]

The basic idea of the method is to compare known losses with used-up premiums. Used-up premiums are obtained as a product of a premium and a lag factor, i.e. the reciprocal value of the loss development factor. A lag factor indicates how much of the final cost of claims incurred in the year *i* is known on the valuation date.

Final losses for the period of occurrence *i* according to the Cape Cod method are estimated as follows:

$$\hat{C}_{i,n}^{CC} = \hat{L} \cdot \tilde{P}_i , \qquad (8)$$

where:

$\hat{L}$ - correction factor which in fact represents the final loss ratio obtained as a ratio of the estimated amount of total losses and the earned premium for the development period, or expressed mathematically:

$$\hat{L} = \frac{\sum_{i=1}^{n} C_{i,n-i+1}}{\sum_{i=1}^{n} \left(\tilde{P}_i / F_{i,n-i+1} \right)} , \qquad (9)$$

---

[74] *Kočović, J., & Mitrašević, M., & Trifunovic, D. (2019). Advantages and Disadvantages of the Methods for Assessment of Loss Reservations in Non-life Insurance. Yugoslav Journal of Operations Research, 29 (4), pp. 553–561.*

[75] *Buhlmann, H. (1983). Estimation of IBNR reserves by the methods chain ladder, Cape Cod and complementary loss ratio. Unpublished; Stanard, J. (1980). Experience Rates as Estimators: A Simulation of their Bias and Variance, Pricing Property and Casualty Insurance Products. Casualty Actuarial Society Discussion Paper Program, and Review by John Robertson, p. 485.; Stanard, J. (1985). A Simulation Test of Prediction Errors of Loss Reserve Estimation Techniques. PCAS LXXII, pp. 124-153.*

[76] *Straub, E. (1988). Non-life Insurance Mathematics. Springer-Verlag, Zürich: Association of Swiss Actuaries.*

where:
$C_{i,n-i+1}$ - cumulative losses incurred in the year *i* are settled (reported) by the end the year *n-i+1,*
$F_{i,j}$ - loss development factor incurred in the year *i* and settled (reported) by the end of the year *n-i+1,*
$\tilde{P}_i$ - earned premium in the period *i* .

As highlighted by Bühlmann (2016), the loss reserves in this method are much less dependent on changes in the individual value of $C_{i,j}$ than in the chain-ladder method, whereas they are very sensitive to the changes regarding a lag factor.[77]

Mack's chain-ladder model

Deterministic reserving methods, as the most commonly used methods in actuarial practice, yield only a point estimate for loss reserves, but do not provide an insight into the deviation of this estimate from the truly required reserves. Stochastic reserving models allow to determine the standard error of prediction in claims reserving and estimate reserve variability.[78]

Mack defined a stochastic version of the model that uses the chain-ladder algorithm to predict outstanding claims and calculate appropriate claims reserves[79]. The method assumes the existence of accident-year-independent factors f_l ,…, f_{n-1} in such a way that based on the known loss development C_{i1} ,…, $C_{i,j}$, the expected value of $C_{i,j+1}$ is equal to the product $C_{ij\ i}\, f_j$

$$E\left(C_{i,j+1} \middle| C_{i1},...,C_{i,j}\right) = C_{i,j} f_j \,. \tag{10}$$

The model is stochastic beacuse it takes into account not only the expected values, but also the variances of the observations in such a way that the model makes an assumption that for each *i* =1, 2, . . . , *n* and *j* =1, 2, . . . , *n*-1:[80]

$$Var(C_{i,j+1}|C_{i,1},...,C_{i,j}) = C_{i,j}\, \sigma_j^2. \tag{11}$$

---

[77] *Bühlmann, H. (2016). Historical Origin of the Cape Cod Claims Reserving Method. Available at SSRN: https://ssrn.com/abstract=2752387 or http://dx.doi.org/10.2139/ssrn.2752387.*

[78] *Kočović, J., Rakonjac-Antić, T., & Koprivica, M. (2018). Standard Error of Prediction in Claims Reserving: Mack's model. Quantitative Models in Economics, Kočović, J., Selimović, J., Boričić, B., Kašćelan, V., Rajić, V. (eds.), Belgrade: Faculty of Economics, University of Belgrade, Ch. 17, pp. 305-322.*

[79] *Mack T., (1997). Measuring the Variability of Chain-ladder Reserve Estimates. In: Claims Reserving Manual, vol. 2. London: Institute of Actuaries.*

[80] *Merz, M. and Wuthrich, M. V. (2015). Claims Run-Off Uncertainty: The Full Picture. Swiss Finance Institute Research Paper, No. 14-69, Available at SSRN: https://ssrn.com/abstract=2524352 or http://dx.doi.org/10.2139/ssrn.2524352*

An unbiased estimate of the variance $C_{i,j}$ (σ_j^2) can be made based on the following equation:[81]

$$\hat{\sigma}_j^2 = \frac{1}{n-j-1}\sum_{i=1}^{n-j} C_{i,j}\left(\frac{C_{i,j+1}}{C_{i,j}} - \hat{f}_j\right)^2, 1 \le j \le n-2. \qquad (12)$$

The variance for j=n is most often estimated in the following way:

$\hat{\sigma}_{j-1}^2 = \min\left(\hat{\sigma}_{j-3}^2, \hat{\sigma}_{j-2}^2, \frac{\hat{\sigma}_{j-2}^4}{\hat{\sigma}_{j-3}^2}\right)$, and in the case when $\hat{f}_{j-1} = 1$ we get $\hat{\sigma}_{j-1} = 0$.

Generalised linear models

Generalised linear models consist of three components: a random component, a systematic component, and a link between the random and systematic components called a link function *g* (.). In this model, the random component is independent and belongs to one of the exponential families of distributions.

For some functions a(.), b(.), c(.), the density function has the form[82]:

$$f(Y_{i,j};\theta_{i,j};\phi) = e^{\frac{Y_{i,j}\theta_{i,j} - b(\theta_{i,j})}{a(\phi)} + c(Y_{i,j},\phi)}, \qquad (13)$$

where:
θ - natural parameter,
ϕ - dispersion or scale parameter in the exponential family,
$Y_{i,j}$- incremental claims.

The variance can be expressed as:

$$\mathrm{Var}[Y_{i,j}] = \phi V(\mu_{i,j}), \qquad (14)$$

where V() is the variance function.

The mean of incremental claims ($Y_{i,j}$) can be expressed in the following equation:

$$\mu_{i,j} = E[Y_{i,j}] = b'(\theta_{i,j}). \qquad (15)$$

[81] *Siegenthaler, F. (2023). Unbiased Estimator for the Ultimate Claim Prediction Error in the Chain-ladder Model of Mack. Annals of Actuarial Science, 17(1), pp. 118–144. doi:10.1017/S1748499522000082.*
[82] *Hoedemakers, T., Beirlant, J., Goovaerts, M. J., & Dhaene, J. (2005). On the Distribution of Discounted Loss Reserves Using Generalised Linear Models. Scandinavian Actuarial Journal, 2005(1), 25–45. https://doi.org/10.1080/03461230510009727.*

Based on the preceding formulas (14) and (15), it is evident that while the mean depends solely on a natural parameter, the variance additionally relies on a dispersion parameter.

The systematic component of GLM actually represents a linear predictor (η) which can be expressed by the following equation:

$$\eta_{i,j} = \left(R\vec{\beta}\right)_{ij} = \beta_1 R_{ij,1} + \ldots + \beta_p R_{ij,p} \quad i,j = 1,\ldots,n \quad , \qquad (16)$$

where:
$\vec{\beta} = \left(\beta_1,\ldots,\beta_p\right)'$ - a set of parameters,
R- regression matrix of dimensions $n^2 \times p$.

Expected value of incremental claims, which are assumed to be independent and belong to the so-called exponential family of distributions, can be modeled across different periods of occurrence and for a specific development period *j* based on the following equation:

$$g\left(\mu_{i,j}\right) = \eta_{i,j} = \alpha_i + \beta_j \quad , \qquad (17)$$

where:
α_i - parameter for each year of occurrence *i*, *i*=2,3,…,n
β_j - parameter for each development year *j*, *j*=2,3,…,n
g() - monotonic, differentiable, link function that connects random and systematic components.

Equation (17) can also be expressed with an intercept term (β_0):[83]

$$g\left(\mu_{i,j}\right) = \beta_0 + \alpha_i + \beta_j \quad . \qquad (18)$$

The values of incremental claims ($Y_{i,j}$) can be predicted as follows[84]:

$$\hat{Y}_{i,j} = g^{-1}\left(\eta_{i,j}\right) = g^{-1}\left(\hat{\beta}_0 + \hat{\alpha}_i + \hat{\beta}_j\right) \quad . \qquad (19)$$

---

[83] *Renshaw, A.E., & Verrall, R.J., (1998). A Stochastic Model Underlying the Chain-ladder Technique, British Actuarial Journal, Cambridge University Press, vol. 4(4), 903-923; Tee, L., Käärik, M.; Viin, R. (2017) : On Comparison of Stochastic Reserving Methods with Bootstrapping, Risks, ISSN 2227-9091, MDPI, Basel, Vol. 5, Iss. 1, pp. 1-21, https://doi.org/10.3390/risks5010002.*

[84] *Duval, F., & Pigeon, M. (2019). Individual Loss Reserving Using a Gradient Boosting-Based Approach. Risks, 7(3):79. https://doi.org/10.3390/risks7030079, p.4.*

The estimation of the parameters $\hat{\beta}_0, \hat{\alpha}_i$ (i=2,n), $\hat{\beta}_j$ (j=2,n) in the previous equation is performed by maximising the likelihood.

According to Taylor (2019), the reason why GLMs were not widely used in actuarial calculations until the 1990s can be partly attributed to the limitations in computer data processing during that period.[85]

3. APPLICATION OF MACHINE LEARNING FOR SELECTING THE METHOD FOR PROJECTING CLAIM SIZE

In the era of digitisation, sophisticated new technologies provide actuaries with advanced tools for risk analysis, prediction of future events, and optimisation of financial strategies.

Simultaneously with the achievements in the field of artificial intelligence, the question arises to what extent the application of machine learning models can contribute to the accuracy of projecting claims in non-life insurance.

Numerous machine learning models have recently been developed for the purpose of estimating claims reserves. In 2021, Blier-Wong et al. published a review of the literature in the field of machine learning on claims in non-life insurance, highlighting that actuaries prefer a modification of the chain-ladder method[86], which is to be expected when taking into account previously presented data on how much certain reserving methods are utilised in practice.

One such approach is developed by Wüthrich[87] who has extended Mack's chain-ladder model for claims reserving by using a neural network model for the chain ladder factors. Moreover, in 2018 Wüthrich[88] published a paper where machine learning is applied to project claims reserves based on individual claims data as opposed to traditional calculations of claims reserves based on aggregate claims data.

Gabrielli was also interested in the application of artificial intelligence and, consequently, co-authored a paper with Wüthrich using neural networks to generate

---

[85] *Taylor, G. (2019). Loss Reserving Models: Granular and Machine Learning Forms, Risks, 7(3), pp. 1-18. https://doi.org/10.3390/risks7030082.*

[86] *Blier-Wong, C., Cossette, H., Lamontagne, L., Marceau, E. (2021). Machine Learning in P&C Insurance: A Review for Pricing and Reserving. Risks, 9(1):4. https://dx.doi.org/10.3390/ risks9010004.*

[87] *Wüthrich, M. V. (2018). Neural Networks Applied to Chain-ladder Reserving. European Actuarial Journal, 8, pp. 407–36.*

[88] *Wüthrich, M. V. (2018). Machine Learning in Individual Claims Reserving. Scandinavian Actuarial Journal, 25: 1–16.*

individual claims in non-life insurance[89], and in 2019 he proceeded to publish a paper that uses over-dispersed Poisson models as classical parametric loss reserving models and incorporated it in neural network architecture.[90]

To project settled claims, Kuo[91] analyses an aggregate data set using deep neural networks, and the developed approach is called DeepTriangle. In developing the neural network model, he utilizes open-source software packages (specifically R package and TensorFlow) and provides the code necessary to reproduce the results, which are detailed in the paper and available at the Internet address: https://github.com/kasaai/deeptriangle.

The company Willis Towers Watson has developed a machine-led reserving algoritam within their ResQ software.[92] This algorithm utilizes machine learning to select from various reserving methods (CL, BF, CC, and GLM) and their respective parameters.

This approach aims to enhance the accuracy of estimating future claim payments in a way that minimises the run-off function (differences between realised payments and expected payments). The theoretical basis for the development of the machine-led reserving algorithm and the conducted testing, whose results will be presented in the next section, can be found in the paper by Balona & Richman published in 2020[93].

Their procedure involves first selecting a loss development triangle of appropriate size followed by dividing it into a part used for model training and another subset covering the last few calendar years used for performance testing. Finding the optimal predictive model from the set of all possible models is performed by the following evaluation procedure.

Reserves are calculated for the first calendar period in the training set (the green part of the triangle on Figure 2) by calibrating all possible model parameters on the green area plus the first gray diagonal. The first diagonal of realisation (experience) is added to the initial triangle. In this way, the model adapts to the enlarged triangle.

---

[89] *Gabrielli, A., & Wüthrich, M. (2018). An Individual Claims History Simulation Machine. Risks, 6: 29.*

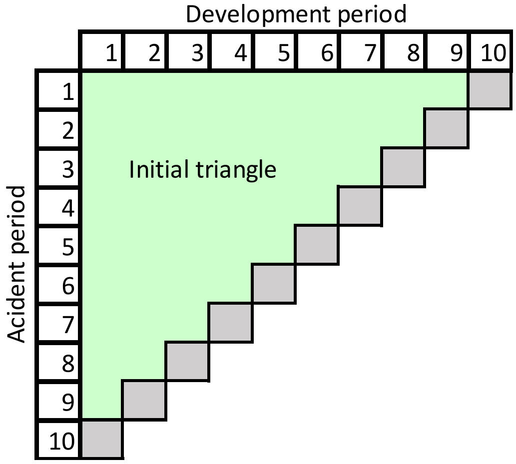
[90] *Gabrielli, A. (2019). A Neural Network Boosted Double Over-Dispersed Poisson Claims Reserving Model. Available online: https://ssrn.com/abstract=3365517.*

[91] *Kuo, K. (2019). DeepTriangle: A Deep Learning Approach to Loss Reserving. Risks, 7: 97.*

[92] *Willis Towers Watson. (2024). ResQ. Available at: https://www.wtwco.com.*

[93] *Balona, C., & Richman, R. (2020). The Actuary and IBNR Techniques: A Machine Learning Approach. SSRN Electronic Journal.*

Figure 2. Illustration of the first iteration of the estimation procedure



Source: Adapted from Balona, C. & Richman, R. (2020). The Actuary and IBNR Techniques: A Machine Learning Approach. SSRN Electronic Journal.

For each subsequent calendar year in the training set a score is obtained for each accident year by calculating Claims Development Result (CDR) and the Actual versus Expected Result (AvE). The optimal predictive model, according to the study applied by Balona and Richman, is the one that minimises the square of the difference between AvE and 0, $(AvE\text{-}0)^2$, which in fact represents the minimisation of the difference between actual and projected claims (the next diagonal) and the minimisation of the square of difference between CDR and 0 $(CDR\text{-}0)^2$, i.e. the difference in the estimation of ultimate claims in successive time periods. Claims Development Result (CDR) is often used to measure run-off (profit or loss) due to the existence of deviations in the estimated value of ultimate claims in successive assessment periods. For the claims incurred in a year *i* and according to the assessment in the calendar year *k* CDR is determined as follows:

$$CDR_i^k = C_{i,n}^k - C_{i,n}^{k-1}, \quad (20)$$

or

$$CDR_i^k = R_{i,k-i}^k - R_{i,k-i}^{k-1} + AvE_{i,k-i}^k, \quad (21)$$

where:

$AvE^k_{i,k-i}$ refers to the actual versus expected (AvE) incremental amount of claims, which is displayed in the subsequent diagonal of the triangle :

$$AvE_{i,k-i}^k = Y_{i,k-i} - \hat{Y}_{i,k-i}^{k-1}. \quad (22)$$

Acknowledging the existence of differences in claims in different calendar years *k*, the CDR score is determined in such a way as to weight the results CDR_i^k with the absolute value of the loss incurred in each year

$$CDR^{k}_{score} = \sqrt{\frac{\sum_{i=1}^{n} \left|Y_{i,k-i}\right| \left(CDR_{i}^{k}\right)^{2}}{\sum_{i=1}^{n} \left|Y_{i,k-i}\right|}} . \tag{23}$$

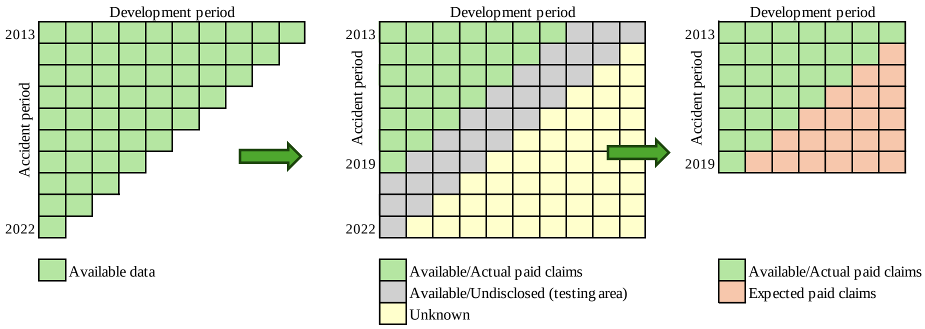
The same approach can be used to determine the score function for AvE.

$$AvE^{k}_{score} = \sqrt{\frac{\sum_{i=1}^{n} \left|Y_{i,k-i}\right| \left(AvE_{i}^{k}\right)^{2}}{\sum_{i=1}^{n} \left|Y_{i,k-i}\right|}} . \tag{24}$$

We refer to these results as the root mean square error (RMSE) of CDR and AvE, respectively.

Afterwards, by expanding the triangle for the following calendar year the reserve assessment procedure repeats. In the third step, the average score is calculated for all calendar years in the subset used for performance testing. In the last stage of the procedure, based on the calculated average score, the method for calculating claims reserves is selected. MSc Miona Graorac, Senior Consultant in the company Willis Towers Watson (WTW), presented to us the experiences in the application of the previously described methodology. In a test called "Beat the Machine Game", conducted in 2023, the results of the application of Machine-led Reserving (MLR) algorithm on large claims databases of the international insurance companies (their clients) were compared with the results of more than a hundred Willis Towers Watson actuaries at the WTW Team Day in Great Britain, divided into more than 40 groups.

Figure 3. Illustration of dividing the available data into subsets



Source: Adapted from the results of WTW Team Day in Great Britain presented in Pratt, T., Mackay, J., & Sappington, J. (2023). The future of reserving (Algorithmic Reserving). Unpublished Materials.

For testing purposes, the data on the incremental claims, selected from the database of several international clients, were used, excluding any other specific details or identifying information related to insurance cases, to ensure data confidentiality. The already existing data from 2013 to 2022 were divided into two subsets.

A larger subset of data from 2013 to 2019 (the green part in *Figure 3*) was used for a training algorithm and given to the actuaries for reserve calculation.

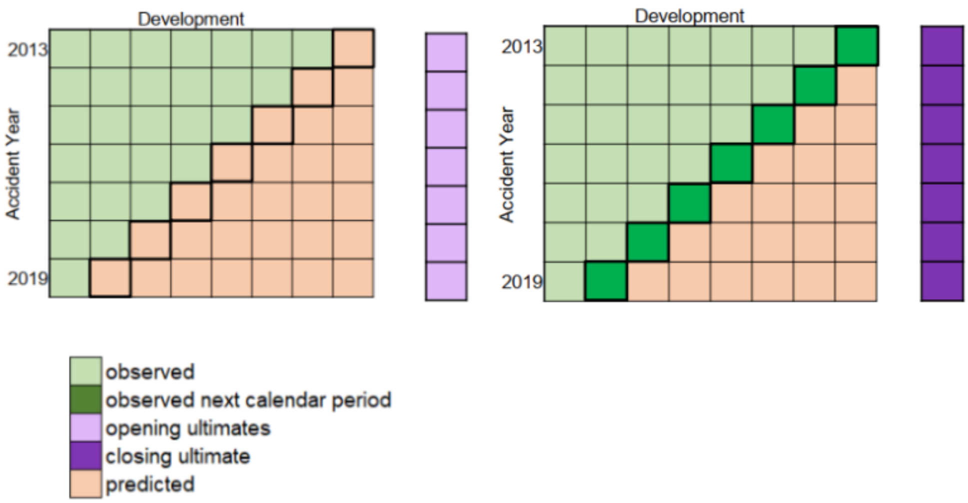
The remaining subset from 2020 to 2022 (depicted in grey in *Figure 3*) comprised the available data used to evaluate and test the performance of both the actuaries and the algorithm, which neither group had seen prior to the evaluation.

The algorithm starts from all possible choices of reserving methods (in this particular study, CL, BF, CC and GLM models were used).

A matrix of all the different modelling options is compiled for each method individually, and afterwards their rating is calculated.

Depending on the specified function of the root mean square error (RMSE) of CDR and AvE, it iteratively passes through all time points and creates an optimal model that minimizes the variation in claims reserves and AvE.

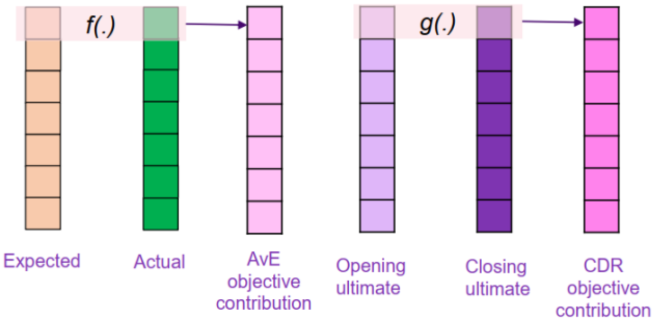
Figure 4. Illustration of the change in reserves for the incurred claims and AvE at the beginning and end of the period



Source: Adapted from the results of WTW Team Day in Great Britain presented in Pratt, T., Mackay, J., & Sappington, J. (2023). The future of reserving (Algorithmic Reserving). Unpublished Materials.

For each subsequent calendar year of the training subset, the root mean square error of CDR and AvE is calculated in accordance with equations (23) and (24), respectively, based on the next diagonal of experience (Figure 4.).

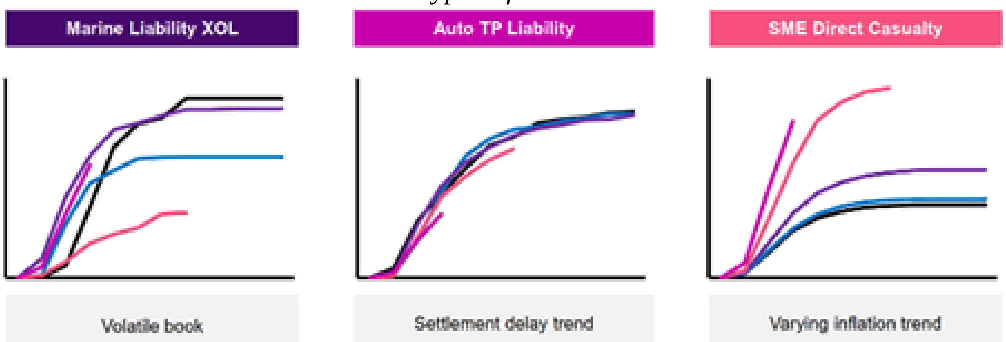
Figure 5. Illustration of calculation of CDR and AvE root mean square error



Source: Adapted from the results of WTW Team Day in Great Britain presented in Pratt, T., Mackay, J., & Sappington, J. (2023). The future of reserving (Algorithmic Reserving). Unpublished Materials.

Consequently, the best-rated model is selected as the minimum of the average score (the smallest Run-Off score: AvE and the smallest reserve volatility: CDR).
For this test, the data of three different types of insurance are selected:
- highly volatile Marine Liability XoL (Excess of Loss) - liability risks for clients with exposures in marine operations,
- MTPL – (Motor Third-Party Liability) - Auto Liability, with a very long claim settlement period, and
- SME Direct Casualty - direct accident insurance for small and medium enterprises with a volatile inflation trend.

Figure 6. Presentation of the dynamics of development of settled claims for the three types of insurance



Source: Selected portfolios for WTW Team Day exercise in Great Britain presented in Pratt, T., Mackay, J., & Sappington, J. (2023). The future of reserving (Algorithmic Reserving). Unpublished Materials.

Figure 6 depicts the development of claims for three selected types of insurance, where on the X axis we have claims development period, and on the Y axis the percentage of the development of settled claims, for each accident year.

The actuaries were given an hour to parameterize the claims, while the algorithm only took a few minutes. The success was measured based on the following results:

$$\frac{(\text{Expected unsettled claims} - \text{Actual unsettled claims})}{(\text{Actual unsettled claims})} \quad (25)$$

Figure 7. The results of "Beat the Machine Game"

Source: Adapted from the results of WTW Team Day in Great Britain presented in Pratt, T., Mackay, J., & Sappington, J. (2023). The future of reserving (Algorithmic Reserving). Unpublished Materials.

Figure 7 depicts the comparative success of the MLR algorithm using quarterly data aggregation[94] (as shown by the pink point) against the performance of the actuarial teams (represented by the blue area). Reserves estimated by actuarial teams, while the grey rectangle displays the weighted mean of all teams. The horizontal line is run-off from zero, i.e. zero deviation from the actual claims. The space above the line represents an overestimation of the reserves, while the results below the line represent underestimation of the reserves.

Only one of the 40 teams was rated better than the algorithm, using the external information that was later incorporated into the algorithm itself. As for the Marine XOL portfolio, the actuaries also show a certain underestimation, whereas the

[94] *The data is available at a lower granularity than the annual one, so both the actuaries and the algorithm are left to choose at which level to perform the calculation.*

"machine" was more successful than almost all actuaries. It is interesting that in the case of Auto Liability (MTPL), MLR managed to achieve a run-off of almost 0%, while the actuaries mostly underestimated the claims. The actuaries most often overestimated portfolio reserves with volatile inflation, while MLR showed a slight underestimation. Overall, the MLR quarterly model proved to be more accurate compared to the annual model.

The application of MLR in this example demonstrated the ability to solve several key problems in claims reserving[95]:

1. **Efficiency**
   Problem: Numerous types of insurance which are not material in terms of premium and claims volume but rather time-consuming regarding parameterisation and verification.
   Solution: MLR automates the preliminary calculation of reserves and helps identify the areas that require attention.

2. **Level of Aggregation**
   Problem: The pressure to aggregate and reduce the number of insurance types, leads to trade-offs and various challenges.
   Solution: When the algorithm is applied at a lower level than the one at which reserves are calculated, it can indicate possible subsets into which the data can be split.

3. **Controlling Experience**
   Problem: Many types of insurance are often neglected based on materiality, potentially resulting in missed business opportunities.
   Solution: It can often be applied to all types of insurance to identify the portfolios that need attention that would otherwise not qualify for in-depth analysis.

4. **Backtesting**
   Problem: Historical deviations based on "actuarial valuation" are rarely audited and confirmed.
   Solution: Backtesting how well each model fits the observed data is implied in the objective assessment.

5. **Validation of Results**
   Problem: A second line of reserve estimation or group validation often involves duplicating efforts to reproduce the reserve calculation.
   Solution: It can be used as a second line of assessment tool for actuaries to check the reasonableness of the calculated reserves and who also perform the primary calculation.

[95] *Pratt, T., Mackay, J., & Sappington, J. (2023). The future of reserving (Algorithmic Reserving). WTW, Unpublished Materials.*

Without neglecting the shortcomings of machine learning models, which are reflected, among other things, such as their complexity and reduced transparency compared to traditional actuarial reserving methods, as underlined by Richman, Rummell, and Wuthrich[96], we can conclude that the previously described approach to the application of machine learning techniques can enable faster data processing. We cannot reject the initial hypothesis that the application of artificial intelligence can contribute to increased efficiency and innovation in the area of non-life insurance claims reserving. It allows actuaries more time to focus on analysis and innovations in the insurance field, thereby enhancing actuarial practice and overall insurance operations, which will be the subject of our further research.

[96] *Richman, R., & Rummell, N., & Wuthrich, M. V. (2019). Believing the Bot - Model Risk in the Era of Deep Learning. Available at SSRN: https://ssrn.com/abstract=3444833 or http://dx.doi.org/10.2139/ssrn.3444833.*