



Prediction of Life Insurance Premium during Pre-and Post-Covid-19: A Higher-Order Neural Network Approach

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Abstract The impact of Covid-19 drastically changed the economical, social, behavioral, and psychological aspects of human life. Just after the official announcement of this pandemic by the World Health Organization, the entire world has locked for several months. As people come across these unpredictable situations, insurance has emerged as one of the ways to financially protect themselves and their families. Consumers were confused in terms of financial gain and risk associated with this disease. In this critical situation, the study on the consumer decision-making process is an integral part to evaluate consumer behavior. An evolutionary improved FLANN is developed to analyze the growth of insurance during the pandemic and observed the insignificance of this pandemic effect on consumer behavior toward life insurance. The proposed study has undertaken an asymmetrical data analysis on 24 life insurance companies of India from January 2015 to December 2020 and predicted the premium collection for the future. The proposed method is compared with other similar machine learning methods and found to be superior.

Keywords Covid-19 · Consumer behavior · Life insurance · Premium · FLANN · Genetic algorithm

Introduction

World Health Organization (WHO) declared the novel coronavirus disease (COVID-19) as a global pandemic on March 11, 2020, just after the official announcement of Chinese authorities on the detection of a fresh kind of virus. India is also a victim of this worldwide epidemic COVID-19 spread by the SARS-CoV-2 (coronavirus). Currently, India has 11,173,761 confirmed cases and 157,584 deaths as of March 05, 2021, which is the second-highest number of confirmed cases in the world after USA.¹ The pandemic has badly affected the economies and businesses across the globe. The announcement of 3 weeks lockdown by the Government of India followed by further extension up to May 3, 2020, curtailed the economy critical for common men. The lockdown, travel restrictions, social distancing, preventive health-care measures massively affected the lives of individuals. The fear of survival has changed the lifestyle of the individual. A preventive measure like a vaccine could be the only lifeline that replaces the new normalcy. However, the inception of the vaccine in Europe, Russia, China, the USA, and India could not able to bring new hopes among the common man. Now they turned their perseverance toward protective measures like Medicaid which can protect human life. Moreover, sanitizer, glove, face mask, or PPE kit could not solve their fear of resistance rather some protective measures like life insurance could help them in an emergency. Covid-19 has shifted the business and economy with unexpected changes never before. Particularly, there became a drift of business

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¹ <https://www.worldometers.info/coronavirus/country/india/>.

from physical transactions to social distancing, isolation, virtual form for life protective measures a sea change observed on consumer consciousness toward life protection. As people come across this unpredictability and its impact on well-laid plans, financial or otherwise, insurance is emerging as one of the ways to financially protect themselves and their families.

Covid-19 accelerated a massive change in the mindset of consumers. Consumers got confused in terms of financial gain and risk associated with this disease. The pandemic is considered a lesson for survival than growth. This critical situation pushes consumer behavior in a different direction. The uncontrollable situation of crisis, partial lockdown, and human interface proclaimed the disastrous economy of the nations indicating a massive change in market dynamics. In the entire world market, consumers are the catalyst for marketing competitiveness and growth. Within this disastrous economy, the consumers understood to manage the crisis; change their needs; develop personality; and integrate the nationality, culture, and time to extend a new form of consumer behavior [1].

Consumer behavior is the internal and external way of thought process that identifies needs, desires, makes the purchase, and consumes the farming and engineering goods, services, housing, and capital [2]. So, consumer behavior is a significant decision-making procedure to evaluate the alternatives and dispose accordingly of them [3]. Consumer behavior can be explained in three different approaches such as psychological, sociological, and economic to define their need. However, people are not the same as their perception varies with economy or crisis [4]. Consumer behavior emerged with new trends in these crisis times. In crisis times, consumer behavior is associated with risk perception and risk attitude. Risk perception is denoted as the risk content, whereas risk attitude provides the consumer's interpretation concerning the risk content. These changes in consumer behavior that occurred due to economic losses may be restrained by characteristics of personality [5]. These all kinds of personalities associated with the risk are performed by the consumers.

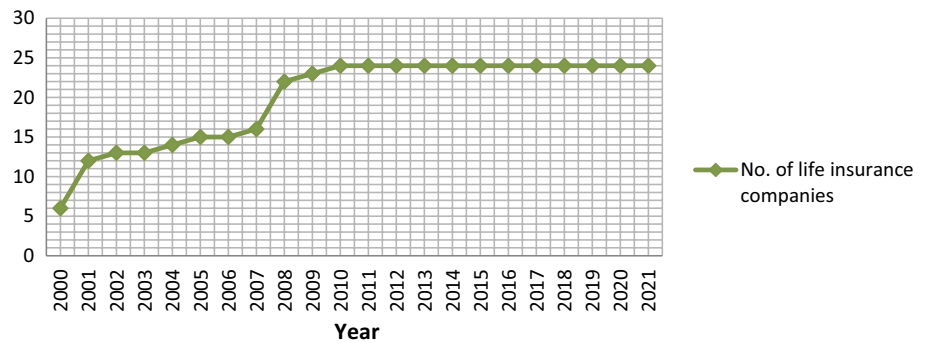
Covid-19 has changed consumer behavior on purchase and consumption patterns. Now consumers are locked and knocked at home. In this crisis, there is a need to understand the best possible way to market the appropriate products and services to the right customer in an effective way. The appropriate way to market the product or service can be only possible through the digital transition as consumers feel insecure. The market leaders perhaps examined the changes in the behavioral pattern of consumers, provided an adequate platform for exchange. They redefined the expectations of consumers by the social sphere and individual orientations enunciated by Maslow's need hierarchy theory. In this demand and supply conditions of the market, the risk associated with health and life could be a major

concern for individual and family protection. So, insurance coverage could be an important asset of every individual life. Research on investment anxiety of financial and insurance decisions is not the new area of research; however, this pandemic taught us socio-psychological factors in the transformation of the behavior of insurance consumers under the influence of the biogenic threat. A study was conducted to measure the investment anxiety and its impact on the insurance behavior of Russian citizens where most of the consumers prefer to purchase on a rainy day in Russia, but this pandemic changed the psychological behavior. In other aspects, it was observed that women feel low financial confidence than men to buy insurance products [6].

In most countries, consumers hesitate to purchase insurance products. They need faith and assurance in the insurance companies. Moreover, insurance awareness is also a critical reason for not buying an insurance product. The author [7] revealed that there is negative behavior toward insurance companies in Nigeria. The theories of reasoned action (TRA) have examined the low influential rate of life insurance companies. It observed that individuals who are worried about early death are more likely to purchase life insurance. About one-third of the consumers do not think to be exposed to the risks of disability, death, and critical illness shortly and nearly 20% of non-policy holders have pessimistic about life insurance. Therefore customer loyalty programs like customer relationship management and new technological strategies should be initiated by the insurance companies. The study examined the interventions of foreign companies captured the insurance market in Ireland where the limited scope is also not available for the local market. Thus, insurance companies are facing greater challenges in distinguishing their product from others in the marketplace [8].

According to various studies, the insurance market is volatile. It may be influenced by psychological, economical, or behavioral factors but consumers act within their attitude toward insurance products. The entire insurance market is controlled by shared values and cultural influence to remove the barriers of marketing communication. In his study, Chan [9] examined that the burgeoning Chinese insurance market is more influenced by money management rather than risk management. Hence, it is necessitated to remove all the cultural barriers to enhance a new economic practice to enlarge the life insurance market in China. In the crisis period, the investment anxiety of consumers who are locked inside the home without employment may not opt for insurance. They may consider it as extra pressure within their capacity. But recent studies proposed the role of emotion on insurance decisions. Most of the empirical results denoted the demand for insurance products consistent with the neoclassical theoretical outline by the demographic and economic character of individuals as the term of rational need for insurance.

Fig. 1 Growth in the no. of life insurance companies over the year



However, a few studies considered psychographic factors on insurance decisions. Keeping in mind there is a need for empirical investigation for insurance decisions that measures psycho-physiological factors affecting the emotions, psychological traits, and other socio-economic variables to predict insurance demand among consumers [10].

The last decade has witnessed some of the statistical methods for the above mentioned analysis. Although some of the methods are found to be significant, the majority of such methods possessed certain pitfalls. This laid the foundation of intelligent computing-based methods for predicting uncertain behaviour (Fig. 1).

Rao [11] articulated the future procedure of statistical tools in areas of human attempt from scientific research to optimum use of resources for social welfare, prediction, and decision making. He observed the controversies that arise in selections of model data prediction and probabilities in the decision-making process. Moreover, this study emphasizes on the use of statistical models on small datasets became inadequate resulting from a massive intervention of big data, and data mining through the artificial neural network is a matter of concern.

Munge and Otike [12] examined the presentation of library service through the use of quantitative data interpretation. They observed that quantitative data could not provide an accurate result unless the library service was measured qualitatively. Hence it is noted that quantitative measures do not demonstrate the value of a library service for which computational measurement is needed.

Ly et al. [13] hypothesized that the social science researchers are increasingly using statistical models to illustrate conclusions from information and very often focusing on only the number ‘p’ which intercepts beyond a single number preference. Now Bayesian paradigms brought the use of the open-source software program JASP which can give a complete Bayesian reanalysis from normally reported summary statistics. Hence the uses of conventional statistical results have converted into software applications.

Bajaj et al. [14] examined that machine learning has been a competent mechanism to train, map, analyze, and predict datasets properly. In their paper, they used the regression

techniques, a supervised machine learning approach to assess the time series data of Covid-19 for comparing the datasets of Kerala, India, and two municipal corporations of Maharashtra to examine the controlling process of the authorities. They found that the level of control was differing from the nation to the regional locality. The regional area is considered to be cubic for total Covid-19 cases and multi-peak Gaussian for active cases. To maintain the difference in opinion of the statistical measurement, they utilized the SciDAVis (Scientific Data Analysis and Visualization), a cross-platform program for graphical presentation of datasets and data analysis that supports linear, nonlinear, and multi-peak functions. It has a built-in operation for all column/row statistics, convolution, and filtering operations with a user-friendly interface. Therefore, this software will be utilized for any kind of analysis where all kinds of nonlinear analysis.

Bajaj et al. [15] conducted a study to predict the effect of Covid-19 on the patient’s database of India and three municipal corporations of Maharashtra. The statistical data have been analyzed and compared with modified susceptible-infected-recovered (SIR) and logistic models at both the national and municipal levels. In their study, they found the superiority of SIR against the logistic model for prediction analysis of Covid-19 cases. Further, they suggested that the modified SIR model gives accurate predictions for 14 days and is limited for changes in government policies or other reasons. Therefore, it could be seen that supervised machine learning approaches are accurate prediction methods to analyze the data in a systematic process.

From the above research, it is evident that most of the researchers suggested the use of the computational method for consumer behavior analysis. Especially neural network-based methods became the main limelight in the twentieth century for solving a most real-life problems. The neural network model is encouraged by most of the neural architecture of the human brain following the neuro-physical structure on decision making of the human brain and from a statistical point, it is closely related to generalizing linear models. However, artificial neural networks are nonlinear and use different estimation procedures (like feed-forward and

backpropagation) rather than traditional statistical models (like least squares or maximum likelihood). In most cases, neural networks have proven to be an important tool for marketers concerned with forecasting consumer choice and giving superior forecasts regarding consumer decision making. Keeping view into this research, an evolutionary improved FLANN model is developed for effective consumer behavior analysis toward life insurance.

The major contributions of this work are:

- (i) Functional link higher-order neural network is proposed for analyzing the consumer behavior toward the insurance policies of pre and post-pandemic situations.
- (ii) An evolutionary optimization (Genetic Algorithm) is used to optimize the parameters of FLANN for efficient performance.
- (iii) Deep investigation on the consumer behavior toward life insurance in the era of Covid-19, where most of the consumers are aware of their life and security than financial flexibility.
- (iv) The study is supported with rigorous experimentation with existing data of 24 insurance companies that provides life insurance facilities to the consumer in general and a detailed analysis examined on consumer behavior toward insurance products in this current situation of the pandemic.
- (v) The performance of the proposed model is compared with other state-of-the-art models to visualize the superiority in prediction.

Review of Literature

According to a study done by Wagner et al. [16], in the area of online retailing in which it was stated that online retailing can be categorized into 4 different e-commerce types. This work propels showcasing exploration and performs by delineating that both technology-related quality and the context-related situational advantage influence buyers' usage of e-channels. Additional discoveries show that retailers can improve purchasers' shopping encounters by giving elective e-channel touchpoints (i.e., explicit computerized shopping designs) that add distinctively to the online client venture. Pillai et al. [17] mentioned that there exists a connection between the probability of shopper spending on items/administrations and dread because of Covid-19. There does not exist any connection between age and the probability of expenditure across various item classifications. All age bunches are carrying on likewise in receiving low touch/computerized exercises and expectation in spending across various item classifications. Sarmad et al. [18] in their study in Pakistan determined that many people are not aware of the insurance services and their importance as "Islam doesn't

allow any investment interest," people considered the insurance services to be against the Islamic rules. They suggested that the "Government must organize seminars to aware the people and disseminating the knowledge of insurance and encourage them to invest in the insurance sector."

Prasad [19] in his paper researched to determine the types of non-life insurance preferred by Indian consumers and their brand shifting behavior for better choices. The outcomes show that buyers seem questionable when there is a nonappearance of a brand; non-brand-arranged buyers' credit more noteworthy significance to the qualities of an insurance policy, with an accentuation on those that identify with the offices (Association, esteem, conduct, and so on). The authors [20] investigated the consumer's perception and their purchase behavior toward health insurance plans in Hyderabad, India. It was found in their examination that financial variables, people's perceptions, and character (personality) qualities instigate the health insurance purchasing behavior of the consumers in the area. Narayanan [21] in his paper did a relative examination of the impacts of segment factors (educational qualification, occupation, age, gender, family income, etc.) on the consumer loyalty of the medical coverage policyholders of public and private area general insurance agencies. The study found that there is huge relationships exist between all segment factors aside from the control of the respondent and a large degree of consumer loyalty with the administration quality in the case of public sector general insurance companies. It is also recommended that the overall insurance agencies ought to consider these segment factors to build a general degree of consumer loyalty with the administration quality as each client is unmistakable regarding their requirements and needs. Rizwan et al. [22] investigated the factors that impact the consumer purchase intentions toward health insurance in the UAE and found that factors like insurance premium, service quality, and convenience are the important factors that influence consumer purchase in UAE.

In the research paper by Safara [23], the effect of COVID-19 on consumer behavior has been investigated. A prediction model was proposed to envision buyer conduct in web-based shopping in the COVID-19 pandemic. Five types of models were inspected, where the decision tree accomplished the best aftereffect of 94.6% precision. Various classifiers could likewise be utilized for the expectation of better exactness. In expansion, a dataset with more highlights influencing from COVID-19 pandemic could be utilized to develop forecast models.

Leong et al. [24] in their study intended to inspect the impacts of demographic factors where F-commerce utilization, web usage theory, and trust transference theory practices were used for anticipating the f-business in the real-life business world. The authors have experimented with the results through ANN and discovered that buyers' experience

was the most grounded indicator followed by the use of Facebook, the impact of hedonic motivation, browsing, age, trust inspiration, interest, inspiration, number of kids, monthly payment, and instructive level. The study proposed that hypothetical and administrative commitments were accommodated by researchers and specialists off-business.

Borimnejad and Samani [25] studied consumer behavior on model-packed product demand utilizing the ANN model instead of conventional and parametric methods. They observed that the ANN model could be able to estimate the demand curve and own-price elasticity for fruits and vegetables packed products in Tehran. The study again revealed that some of the demographic variables and also conventional economic variables like price and income influence the customer's choices. Further, it is suggested the model should be included in the market segmentation and target definition to find accurate results.

Mai et al. [26] conducted a study to examine the purchase intention of consumers toward life insurance and the results displayed that purchase intention, attitudes, financial insight, and product accessibility influence the purchase behavior toward life insurance. The study also revealed that prior financial knowledge could elevate purchasing expectation to genuine buying behavior concerning life insurance. According to Sneha [27], subjective norms have a significant impact on the purchasing behavior of customers toward life insurance policies, social norms also influence the choice of insurance purchase but this may result in inappropriate decisions where the consumers may buy insurance policies which may not fulfill their financial requirements. Viswanathan et al. [28] examined the e-loyalty relationship concerning online life insurance where the role of e-service quality, social influence, and e-customer satisfaction could maintain relationship management. The study revealed that service quality and social influence have a considerable relationship with customer loyalty and satisfaction toward online life insurance plans. Further, it observed that E-customer satisfaction was also an integral part of customer loyalty. Hence, it must maintain a harmonious relationship between the customers when it happened online also.

Kalaichelvan [29] examined the level of awareness and purchase behavior toward life insurance policies among the policyholders. The outcome decides the way that practically all the traits under client awareness toward the promotional methodologies implemented by the life insurance organizations are significant and the most impacting factors are recognized as awareness toward promotion and the benefits through promotion of the respondents.

Ranjan et al. [30] made an effort to discover the impact of technology on the buying behavior of customers in context to life insurance plans. It was found that different channels of distribution do not have a similar degree of acceptance and the policyholders' preference regarding the choice of the

delivery channel as per age group. Significant differences were also observed regarding the choice of distribution channel in the case of other demographic variables like the educational qualification and their profession but concerning "residential location," no significant difference was found in context to the choice of distribution channel.

Chark et al. [31] used a behavioral model to determine how the customers would utilize the premium as the main cue in the context of purchase decision making of insurance. The model implied that there are inverted associations that exist between the insurance demand and the premium, i.e., the demand is declining at high premium levels and vice versa.

Nebolsina [32] investigated that the Covid-19 pandemic has severely affected the insurance market in the USA. The study revealed that the demand for the insurance market is expected to increase 2–6 times with an overall growth of 0.3–7% of US GDP in 2019. It is also suggested to develop public–private protection schemes to secure pandemic-related losses. In this paper, the author examines the business interruption by employing panel vector autoregression (PVAR) to 50 sets of panel data for 3 different periods. In the first instance, the data collected through Google trends hit with a keyword business interruption insurance (BI) and reduced to a single scale by the US states only. Further, the data were collected with endogenous variables in the built model for unemployment insurance. In the constructive model, exogenous variable new Covid-19 cases were also compared with other disasters. It observed that there was a significant relationship between Google trend hit and initial claim.

Altarawneh et al. [33] found that prediction and analysis of financial data-like insurance premium are a difficult task for any time series data. In their study, they examine the stock prices performance of ten insurance companies of Jordan using higher-order nonparametric Exponential Decay Weighted Average (EDWA). They compared the pre- and post-Covid-19 stock market position and found that a range of error measures was found including MAE, MAPE, MPE, ES, and TS. However, the nonparametric test EDWMA was found suitable to predict the stock market performance of various insurance companies where no initial errors have been identified. Further, it suggested that the statistical analysis like EDWMA may have nonsignificant errors while measuring the pre- and post-Covid-19 data analysis of stock index position of different insurance companies across the world (Table 1).

Theoretical Background

Functional Link Neural Network (Fig. 2) is a flat network comprising of two phases: (i) functional expansion of input,

Table 1 Summary of the previous studies

Sl No	Contribution	Result/outcome	References
1	Consumer behavior toward multichannel e-commerce	Consumer behavior on e-channel touch points	[16]
2	The shopping behavior of customers due to covid-19	No significant impact of covid-19	[17]
3	Awareness of the people toward insurance services in Pakistan	Religious impact on consumer	[18]
4	Preference toward insurance	Non-life insurance	[19]
5	Perception toward insurance	Positive perception observed	[20]
6	Consumer loyalty on private and public insurance company	Public sector has positive impact	[21]
7	Purchase intention of consumers	Buyers intention affected by different factors	[22]
8	Purchase intention of consumers toward life insurance	Emotional and rational attitude reflects purchase	[26]
9	Role of online life insurance	Quality of service	[28]
10	Impact of technology vs demographic variables for a purchase decision	Demographic variables such as residential location have no technological impact	[30]
11	Premium as an important cue for insurance decision making	An inverted relationship was found between the ‘insurance demand’ and the ‘premium’	[31]
12	Service quality vs switching costs	Switching costs have greater influence on consumer loyalty	[34]
13	Service delivery by insurance companies	Individual agent	[35]
14	Consumer attitudes on services delivery	Attitude signifies with age	[36]
15	Intrinsic value and brand trust	Relationship marketing	[37]
16	Factors responsible to purchase a life insurance	Consumer behavior is important for decision making	[38]

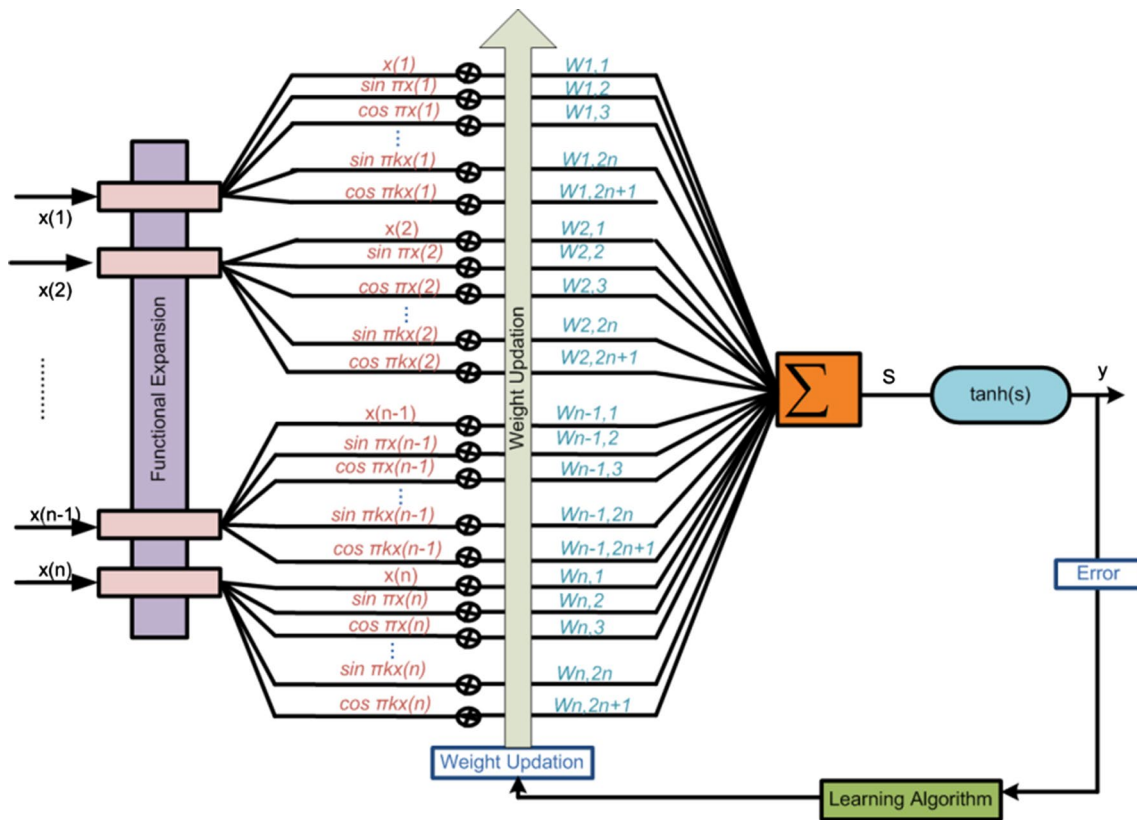


Fig. 2 FLANN architecture

where all the input values are functionally expanded, and (ii) feed-forward phase, where the expanded input is processed

in the flat network in the presence of weights and the output of the network is obtained by using the tan hyperbolic

Fig. 3 Chromosome representation of GA



activation function. Let $X = x_1, x_2, \dots, x_n$ be the dataset with the number of inputs. The i th input $x_i = \{x_{i,1}, x_{i,2}, \dots, x_{i,m}\}$ has m number of attribute values. $\varphi(x_i)$ (Eq. 1) represents the functional expansion of the input vector x_i . Here $\varphi(x_i(j))$ (Eq. 2) is the functional expansion of j th input value in the input x_i . Similarly, the functional expansion of the dataset can be realized as in Eq. 3.

$$\varphi(x_i) = \{\varphi(x_i(1)), \varphi(x_i(2)) \dots \varphi(x_i(m))\} \tag{1}$$

$$\varphi(x_i(j)) = \{x_i(j), \sin \Pi x_i(j), \cos \Pi x_i(j), \sin 2\Pi x_i(j), \cos 2\Pi x_i(j) \dots \sin k\Pi x_i(j), \cos k\Pi x_i(j)\} \tag{2}$$

$$\varphi(X) = \{\varphi(x_i)\}_{i=1}^n \tag{3}$$

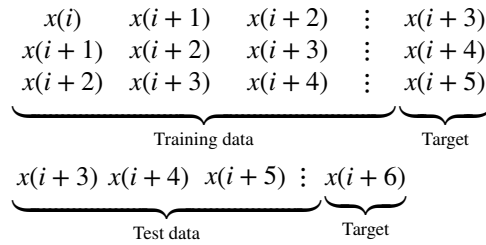
The output of the FLANN network for each $\{x_i\}_{i=1}^n$ is obtained through the following steps:

- i. Compute $s_i = \varphi(x_i) \times W_i$, where $W_i = \{w_i(1), w_i(2) \dots w_i(n \times (2 \times k + 1))\}$ is the weight vector.
- ii. Apply tanh hyperbolic activation function $y_i = \{\tanh(s_i)\}$.
- iii. Find out the error of the network due to x_i as $e_i = t_i - y_i$.

The network parameter W_i can be adjusted by using error through any learning algorithm [39], and a popular one is gradient descent learning.

Proposed Methodology

In this research, a FLANN model is developed for predicting consumer behavior toward life insurance due to the pandemic. In contrast to the traditional method where the whole dataset is segregated into training and testing sets, a sliding window technique was used to generate the training sets. The window moves one step at a time over the whole time series. On each move, an old data point is dropped from the window and one new data point is included in the window. The data points included in the window are used to form an input pattern. Few input patterns form a training set as shown below.



The immediate next input pattern is used as the test set. Then the input patterns are normalized. Instead of normalizing the whole series, it has been normalized individual training and test sets separately. The sigmoid method was used for input normalization shown as in Eq. 4.

$$x_{\text{norm}} = \frac{1}{1 + e^{-\left(\frac{x_j - x_{\min}}{x_{\max} - x_{\min}}\right)}} \tag{4}$$

where x_{norm} = normalized data point, x_i = current data point, x_{max} = maximum value of the window under consideration and x_{min} = minimum of the window.

The test record is also normalized using the same method, but its value is not used for deriving the x_{max} and x_{min} values (i.e., the target vector may reside outside $[x_{\text{max}}, x_{\text{min}}]$).

Genetic algorithm (GA) [40] is considered as one of the successful algorithms in the history of evolutionary optimization due to its adaptive nature to fit any real-life complex problem. Here, an individual (chromosome) of GA consists of a set of FLANN parameters (i.e., weight and bias vector) as shown in Fig. 3. Each such individual (i.e., chromosome) is treated as a potential solution for FLANN. A set of such chromosomes forms a population. During a generation, each chromosome along with the input patterns is supplied to FLANN, outputs are computed, and error signals are generated. The error signal associated with a chromosome is called the fitness of that chromosome. Less is the error signal, a better fit is the chromosome. The GA operators are applied for exploration and exploitation. The best-fit individuals are selected for the next generation. In this way, the search process goes from generation to generation and finally converges at global optima [41], i.e., best-fit chromosome which is the optimal FLANN structure. Therefore the optimal FLANN is evolved through an evolutionary process. The schematic visualization of an evolutionary FLANN is depicted in Fig. 4. The proposed FLANN-GA model can be realized in Figs. 5 and 6 illustrates the selection of the optimal parameter of FLANN.

The high-level FLANN-GA training is presented as in Algorithm 1.

Fig. 4 Framework of evolutionary FLANN model

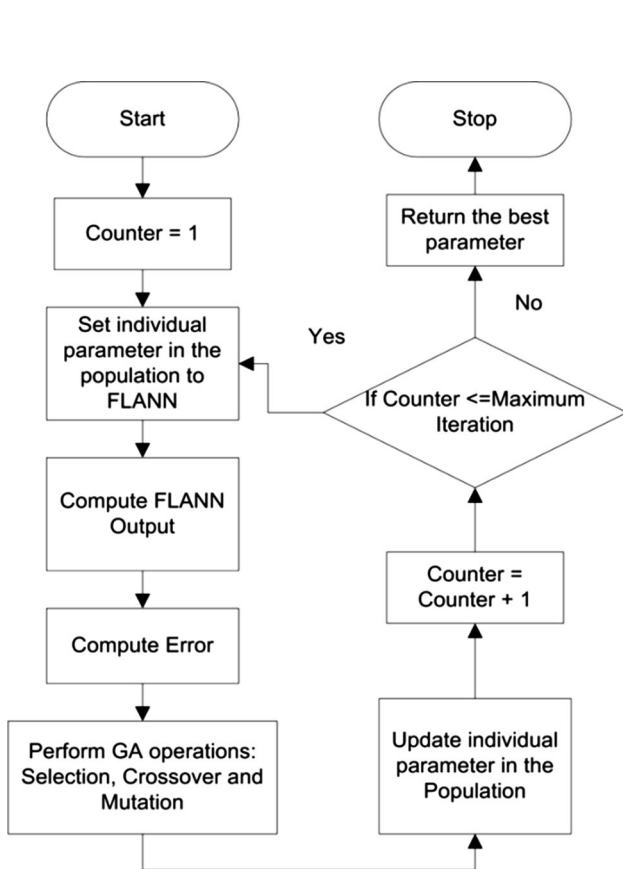
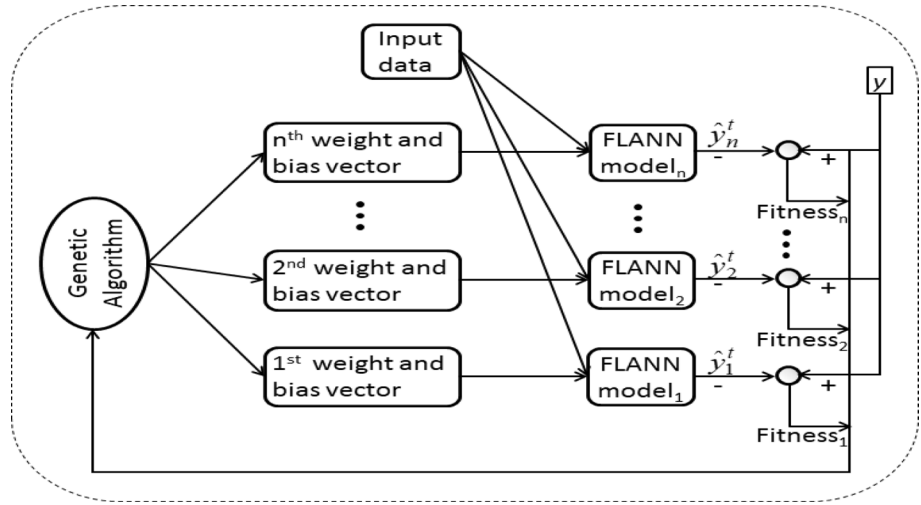


Fig. 5 Proposed FLANN-GA model

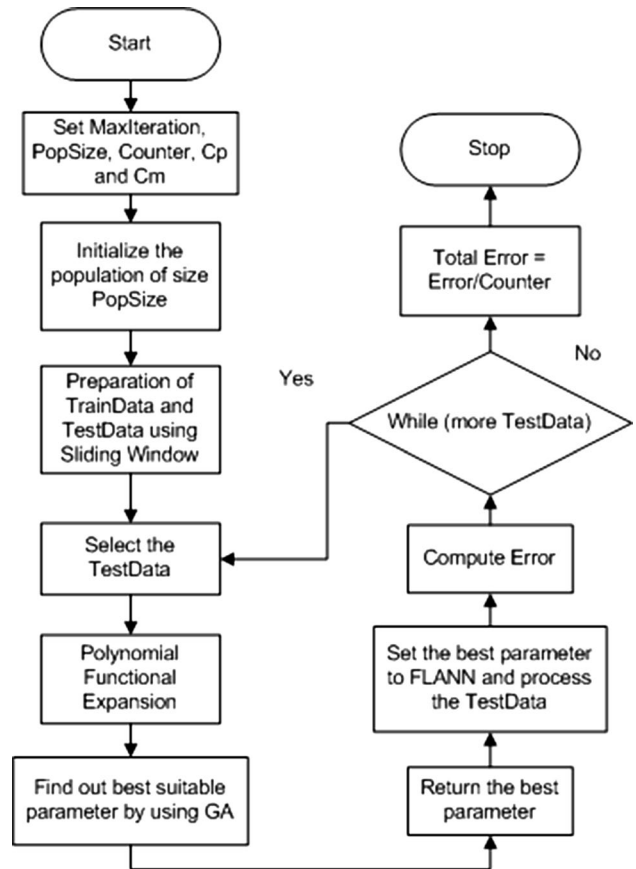


Fig. 6 GA for selection of optimal parameter of FLANN

Algorithm 1: FLANN-GA-based forecasting

1. Set *MaxIteration*, *PopSize*, *Cp*, and *Cm*
 2. Initialize population of *PopSize*
 3. Create *Train* and *TestData* /* Use of sliding window from original time series*/
 4. **While** (more *TestData*)
 - 4.1. Set *Counter* to 1
 - 4.2. Map all pattern according the dimension(from lower to higher), i.e. the values of the features are expanded as per the polynomial basis functions
 - 4.3. Perform Normalization for both *TrainData* and *TestData* /*Applying sigmoid method*/
 - /*Training phase*/
 - 4.4. Set *Iteration* = 0
 - 4.5. **While** (*Iteration* <= *MaxIteration*)
 - Present *TrainData*, and GA *individual* to FLANN
 - Compute FLANN output
 - Error = target – FLANN output
 - Apply GA search operators for intensification and diversification of the search space
 - Select best fit *individual* and update population
 - Iteration* = *Iteration* + 1
 - 4.6. **End while**
 - /*Test phase*/
 - 4.7. Map test pattern from the lower to a higher dimension
 - 4.8. Present *TestData*, and best-fit *individual* to FLANN
 - 4.9. Estimate FLANN output and calculate *Error*
 - 4.10. *Counter* = *Counter* + 1
 5. **End while**
 6. *Total Error* = *Error* / *Counter* /*preserve total error for performance analysis*/
- Set *MaxIteration* to a small value /*for adaptive learning*/

Table 2 Comparison of MAPE values of all models

Dataset	Models				
	GA-FLANN	FLANN	MLP	ARIMA	MLR
Bajaj Allianz	0.05263	0.07205	0.08723	0.09285	0.08230
Exide Life	0.14006	0.37255	0.42899	0.67731	0.82012
Reliance Life	0.06710	0.06992	0.07207	0.07739	0.08990
SBI Life	0.53328	0.82005	0.84291	0.88902	0.86938
TATA AIG	0.06201	0.06852	0.07291	0.07720	0.08397
HDFC Standard	0.08211	0.08792	0.08890	0.07639	0.09120
ICICI Prudential	0.06472	0.07283	0.08821	0.08302	0.08930
Birla Sunlife	0.03885	0.05266	0.05932	0.06292	0.06892
Aviva	0.05872	0.05899	0.06722	0.06627	0.06982
Kotak Mahindra	0.04229	0.05347	0.05893	0.05877	0.06822
Max Life	0.20053	0.27308	0.39288	0.38082	0.39028
PNB Met Life	0.07261	0.07849	0.07792	0.07892	0.08522
Sahara Life	0.09274	0.13005	0.13005	0.13005	0.13005
Sriram Life	0.70034	0.75338	0.79022	0.78021	0.83291
Bharati Axa Life	0.08749	0.09236	0.09430	0.09593	0.09602
Future Generali Life	0.07723	0.09560	0.09603	0.09202	0.09739
IDBI Federal	0.08137	0.08662	0.08702	0.08788	0.08921
Canara HSBC OBC Life	0.04854	0.06200	0.06403	0.06640	0.07436
Aegon Religare	0.06283	0.08007	0.08290	0.08403	0.08739
DHFL Pramerica	0.10825	0.18875	0.18903	0.18999	0.27901
Star Union Dai-Ichi	0.07528	0.08775	0.08847	0.08893	0.08903
IndiaFirst	0.08684	0.08993	0.09239	0.09340	0.09673
Edelweiss Tokio	0.05417	0.05849	0.06329	0.06833	0.06649
LIC	0.05339	0.07402	0.07730	0.07890	0.08620

Experimental Setup and Result Analysis

This section elaborates the experimental setup and results analysis on the proposed method as well as other comparative analyses with other similar methods.

Simulation Environment

In this experiment, it has been used Intel Core i7 CPU 2.20 GHz, 16 GB RAM, Windows 10 (64-bit), and NVIDIA GeForce GTX 1050 for the experiment. Numerous data analyzing frameworks are as follows: NumPy and Pandas. For evaluating models, Sklearn's preprocessing and metrics modules are useful. For visualization purposes, Matplotlib and Seaborn are employed.

Data Preparation

The dataset collection and observation are the foremost processes of this framework. Thus, the collected dataset is strictly observed in this process to find out the types of information. As a preprocessing step, the data are normalized using the Sigmoid method. The data feature vectors for the training and testing set are split into 80:20 ratio. Moreover,

for making the complete prediction on the data, the performance of all the models is being validated on both the training and testing split.

Performance Analysis and Result Comparison

In the experiment, the sliding window shifts one step forward each time. Only a single updated data point was integrated into the training set, and the oldest data point was removed. Therefore, between two consecutive windows, the change in nonlinearity behavior may not be significant. Due to this reason, the early optimized weight unit has been used instead of other random weights for succeeding training. This kind of training is called as adaptive model training. Likewise, after the first training set, it was set the number of iterations to a small fixed value. Since the number of iterations decreases, the training time is reduced significantly. It has been used 17 binary bits to encode a weight value; therefore, the gene size is 17. A collection of chromosomes forms a population. In this experiment, the population size is 50, crossover probability (c_p) is set to 0.6, and mutation probability (c_m) is set to 0.03. The selection process followed an elitism method. The iteration number for the first training set is 50, and for the subsequent training sets, it is

Table 3 Comparison of ARV values of all models

Dataset	Models				
	GA-FLANN	FLANN	MLP	ARIMA	MLR
Bajaj Allianz	0.04309	0.04555	0.04763	0.04890	0.04882
Exide Life	0.06325	0.06887	0.07220	0.07336	0.07690
Reliance Life	0.07328	0.08005	0.08276	0.08390	0.08790
SBI Life	0.06337	0.06884	0.06902	0.07299	0.07837
TATA AIG	0.03682	0.03683	0.04289	0.04622	0.07329
HDFC Standard	0.05384	0.05849	0.06382	0.06452	0.06982
ICICI Prudential	0.07283	0.07775	0.07893	0.07888	0.08452
Birla Sunlife	0.05351	0.07385	0.07653	0.07876	0.08326
Aviva	0.10063	0.17937	0.18455	0.18893	0.19278
Kotak Mahindra	0.06287	0.06836	0.06909	0.07865	0.08276
Max Life	0.04827	0.05306	0.05509	0.05874	0.06390
PNB Met Life	0.05355	0.05849	0.06642	0.07263	0.07655
Sahara Life	0.03588	0.04206	0.04487	0.04678	0.04890
Sriram Life	0.06367	0.06849	0.06985	0.06898	0.08445
Bharati Axa Life	0.04839	0.06300	0.06590	0.06390	0.06783
Future Generali Life	0.12065	0.12830	0.16435	0.13290	0.16733
IDBI Federal	0.05444	0.06738	0.06893	0.06899	0.07356
Canara HSBC OBC Life	0.04839	0.05007	0.06233	0.06344	0.06378
Aegon Religare	0.05384	0.05759	0.05849	0.05887	0.05759
DHFL Pramerica	0.04388	0.05233	0.05785	0.05890	0.05843
Star Union Dai-Ichi	0.05837	0.06305	0.06467	0.06578	0.06877
IndiaFirst	0.04899	0.05302	0.05578	0.05688	0.05876
Edelweiss Tokio	0.07036	0.07544	0.07678	0.07544	0.07544
LIC	0.06355	0.06935	0.07649	0.07988	0.07728

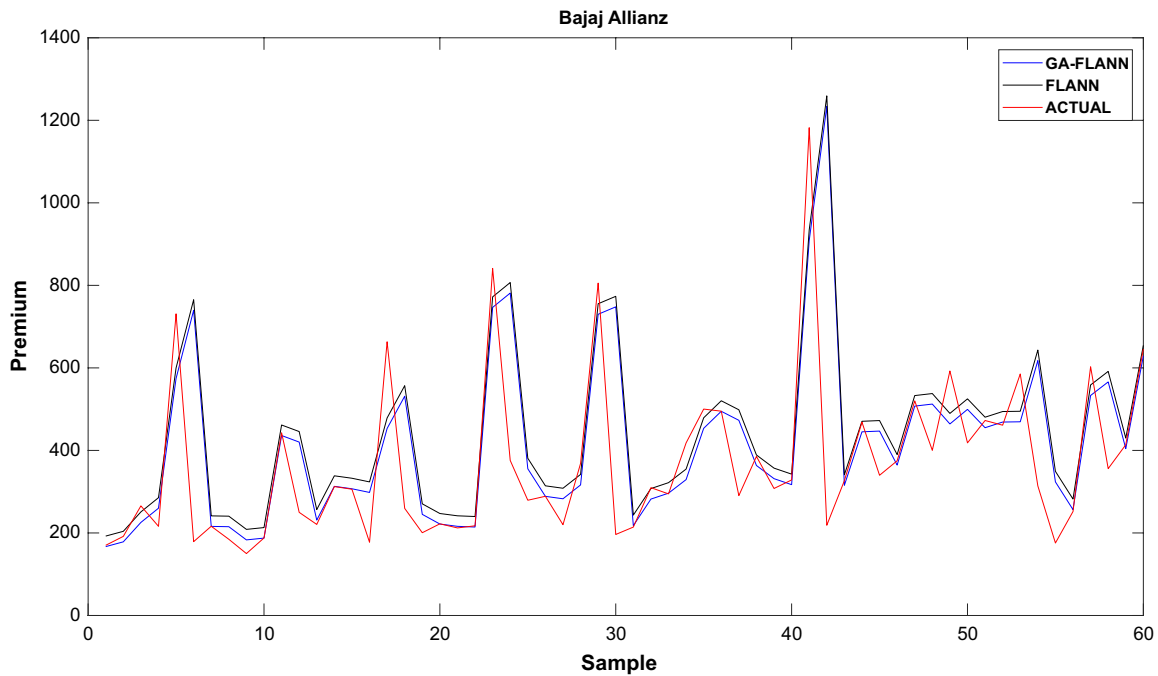


Fig. 7 Predictive result analysis of Bajaj Allianz Life Insurance Company

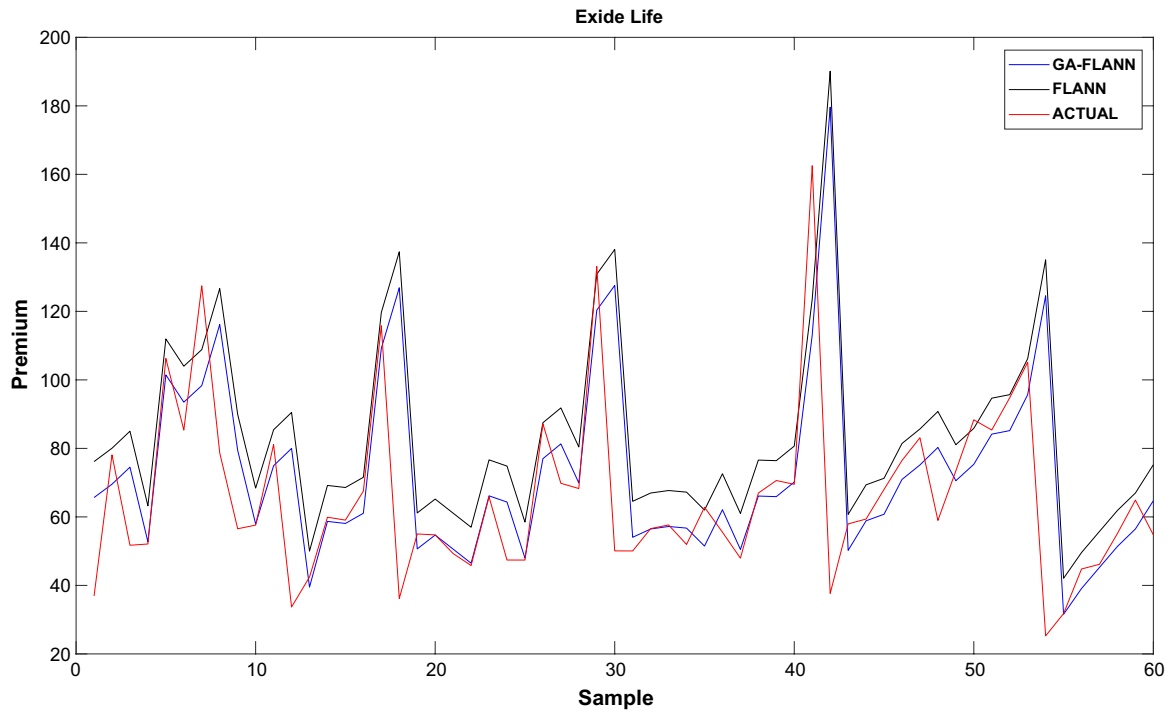


Fig. 8 Predictive result analysis of Exide Life Insurance

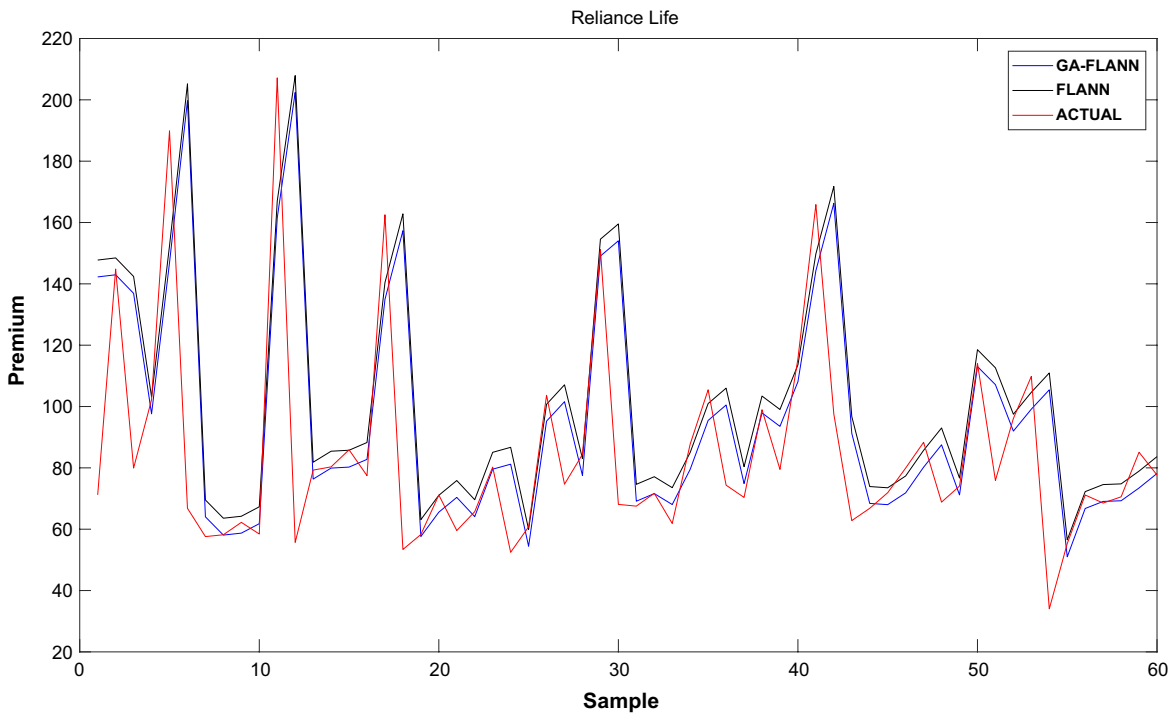


Fig. 9 Predictive result analysis of Reliance life

set to 5 only. The training and test datasets are the same for all seven models. For each dataset, every model is simulated twenty-five times and the average has been considered for

proportional analysis. The mean absolute percentage of error (MAPE) is considered as the performance metric as shown in Eq. 5.

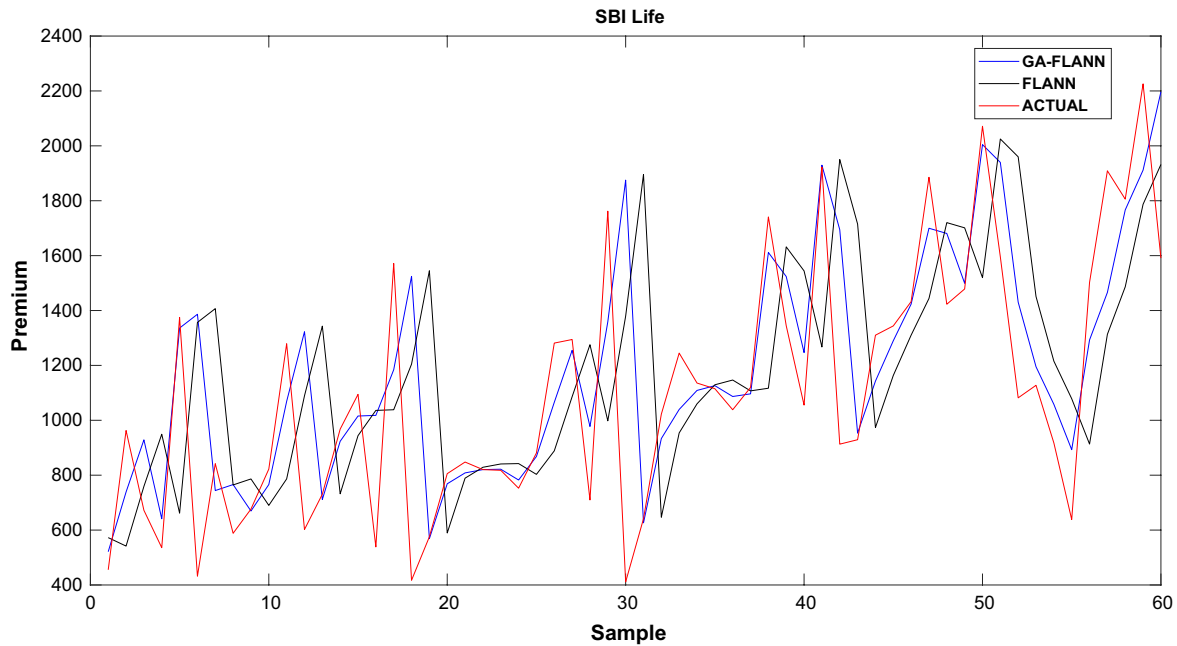


Fig. 10 Predictive result analysis of SBI life

$$MAPE = \frac{1}{N} \sum_{i=1}^N \frac{|Actual_i - Estimated_i|}{Actual_i} * 100\% \tag{5}$$

The MAPE values generated by three models from all datasets are summarized in Table 2. The closer the MAPE values are to zero, the better is the forecast. It has been used another metric Average Relative Variance (ARV) for measuring the accurate directions of the prediction as follows:

$$ARV = \frac{\sum_{i=1}^N (\hat{x}_i - x_i)^2}{\sum_{i=1}^N (\hat{x}_i - \bar{X})^2} \tag{6}$$

In the above equation, x_i is the actual price, \hat{x}_i is estimated price, N is training size, and \bar{X} is the mean of the dataset. The closer the values of these metrics to zero, the better is the forecast (Table 3).

In the present analysis, the data from 24 insurance companies are collected from January 2015 to December 2020. The insurance premium collection in every month and its growth was observed up to the month of recession and impact of Covid-19. In January 2015, Bajaj Allianz Life Insurance Company has had a good start of premium collection about INR 274.67 crore and suddenly reduced to INR 191.72 crore in January 2016. In January 2017, it increases its premium to INR 312.43 crore and again it falls to INR 288.89 crore in January 2018. In January 2019, it collected INR 385.41 crore and increased its premium to INR 418.32 crore in January 2020; however, in April 2019, it collected around

INR 1182.11 crore premiums, and thereafter the premium collection declined due to lockdown (Fig. 7).

Exide Life Insurance has a rollover premium collection from January 2015 to December 2020 (Fig. 8). It had good business of INR 77.26 crore in January 2015, INR 78.11 crore in January 2016, INR 59.91 crore in January 2017, INR 87.16 crore in January 2018, INR 66.96 crore in January 2019, and INR 88.34 crore in January 2020. The premium collection of Exide life was not constant in the entire survey period and observed that from March to December 2020, it had not performed well compared to previous months.

Reliance life is also a premier life insurance company in India, which has no consistent records on premium collections. The data revealed that INR 258.24 crore of premiums were collected in January 2015 which became INR 144.84 crore in January 2016. It has fallen to INR 80.32 crore in January 2017 and rose to INR 103.68 crore in January 2018 (Fig. 9). Again it slumped to INR 98.96 crore in January 2019 and gained INR 114.08 crore in January 2020. It had a good business throughout the year 2020 instead of the covid-19 effect. The premium collection was quite impressive in the lockdown period.

SBI life is also a premier life insurance company under the banner of public sector bank SBI. The company had spontaneous growth of premium collection in the entire period of study. It started with INR 846.81 crore premium collections in January 2015 and closed with INR 1525.96 crore in December 2020 (Fig. 10). At the beginning of 2020,

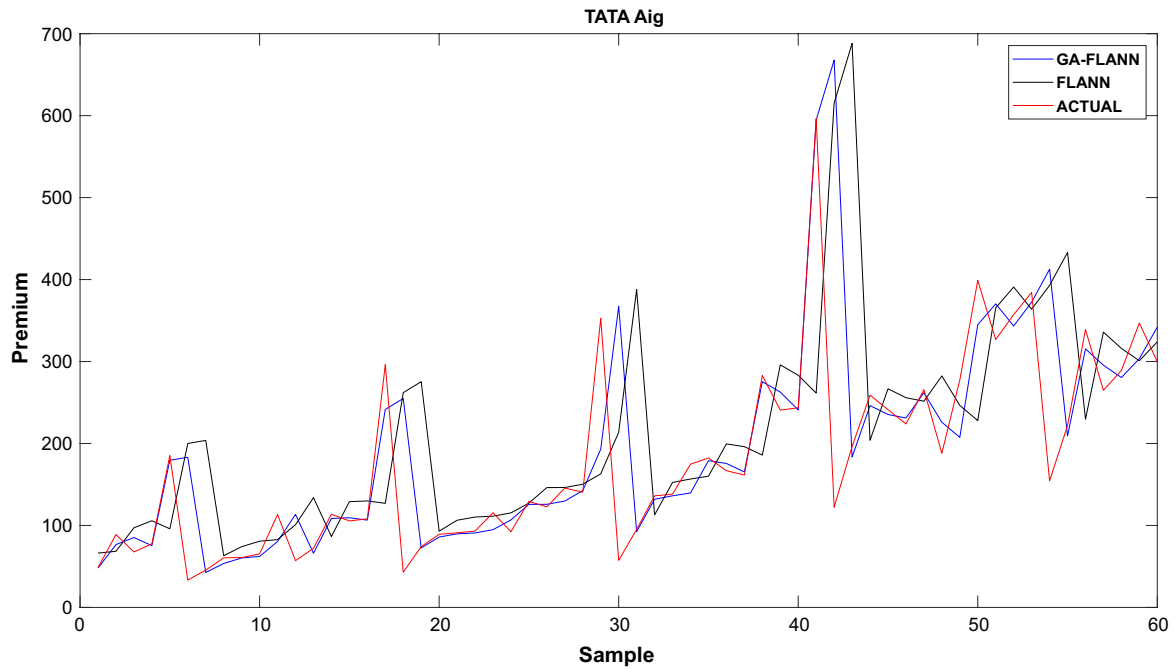


Fig. 11 Predictive result analysis of Tata AIG Life Insurance Company

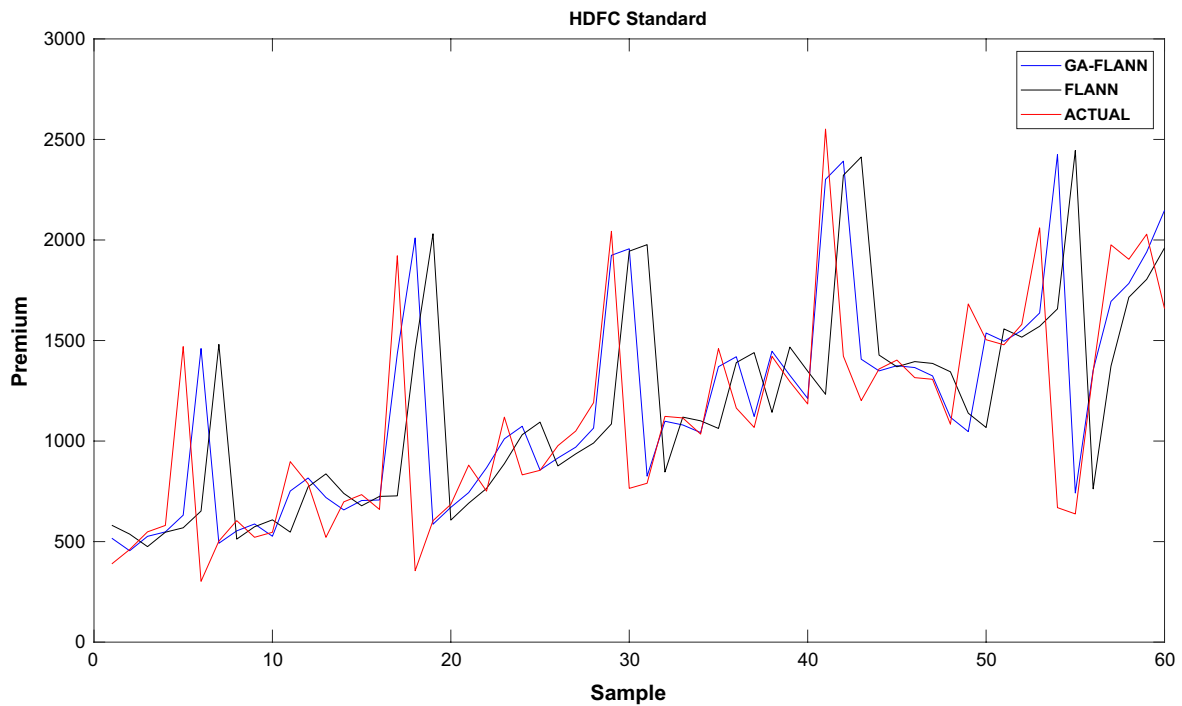


Fig. 12 Predictive result analysis of HDFC life

it had a right start of INR 2071.41 crore in January 2020, declining further due to lockdown.

Tata AIG Life Insurance Company is a leading insurance company in India which have a wonderful premium

collection throughout the survey period. In January 2015 INR 23.91 crore, January 2016 INR 88.89, January 2017 INR 113.73 crore, January 2018 INR 122.73 crore, January 2019 INR 282.99 crore, and in January 2020 INR 399.02

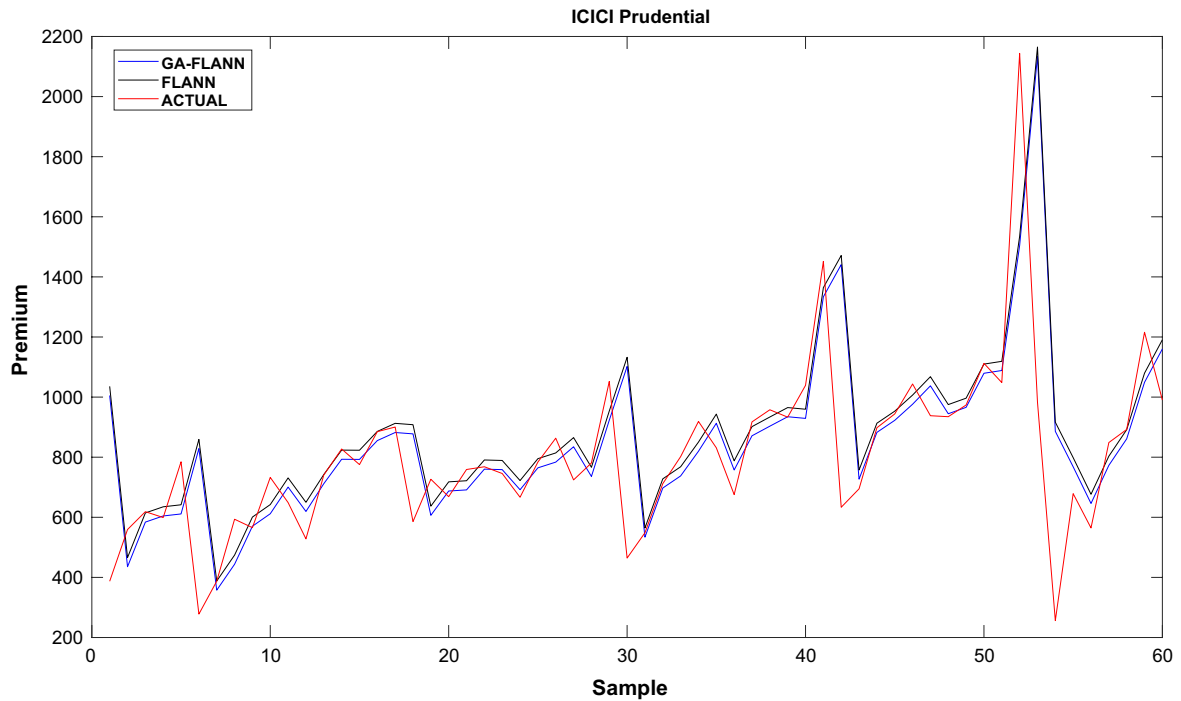


Fig. 13 Predictive result analysis of ICICI Prudential

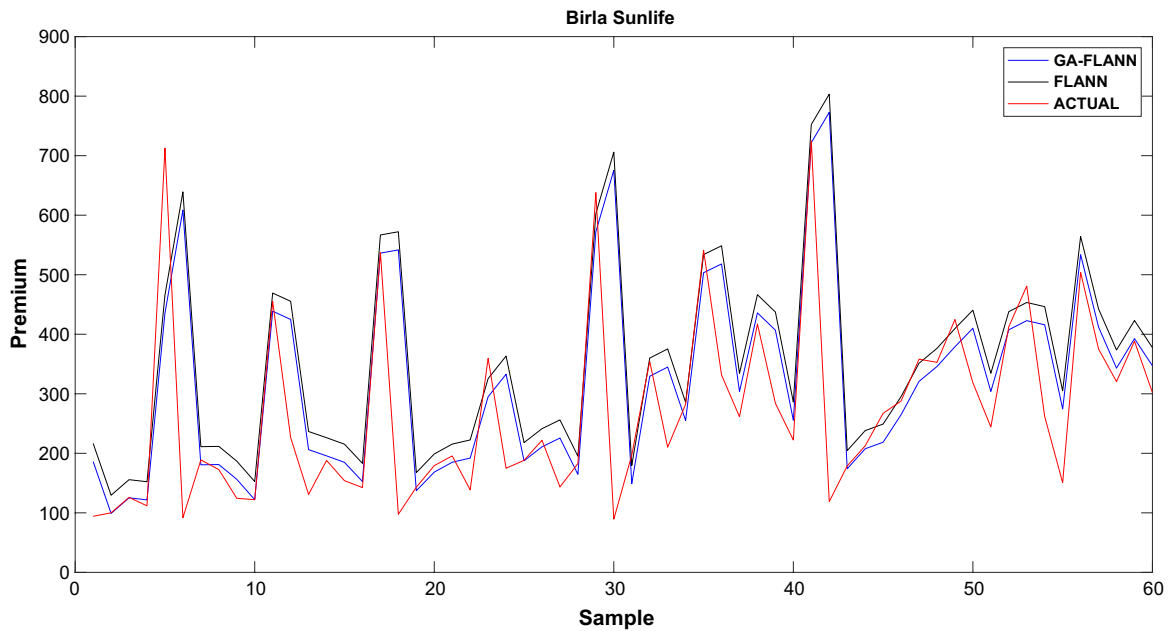


Fig. 14 Predictive result analysis of Birla Sun life

crore, the premium has been collected (Fig. 11). However, the entire period of 2020 was challenging, and the company was not able to maintain consistency and closed its business with INR 287.86 crore in December 2020.

HDFC life is a reputed company in the Indian insurance market. This company is running under the banner of HDFC Bank. As it is the sister concern company of HDFC Bank, it has a good move in the premium collection from 2015 to 2020. Particularly in March every year, the premium

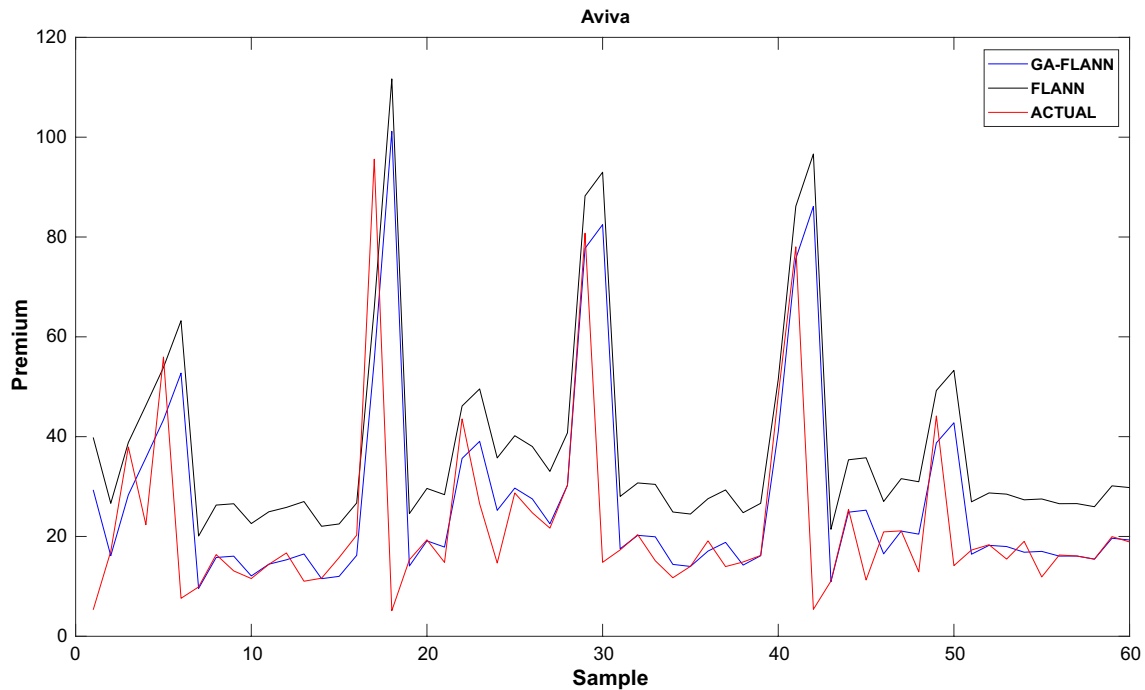


Fig. 15 Predictive result analysis of Aviva life

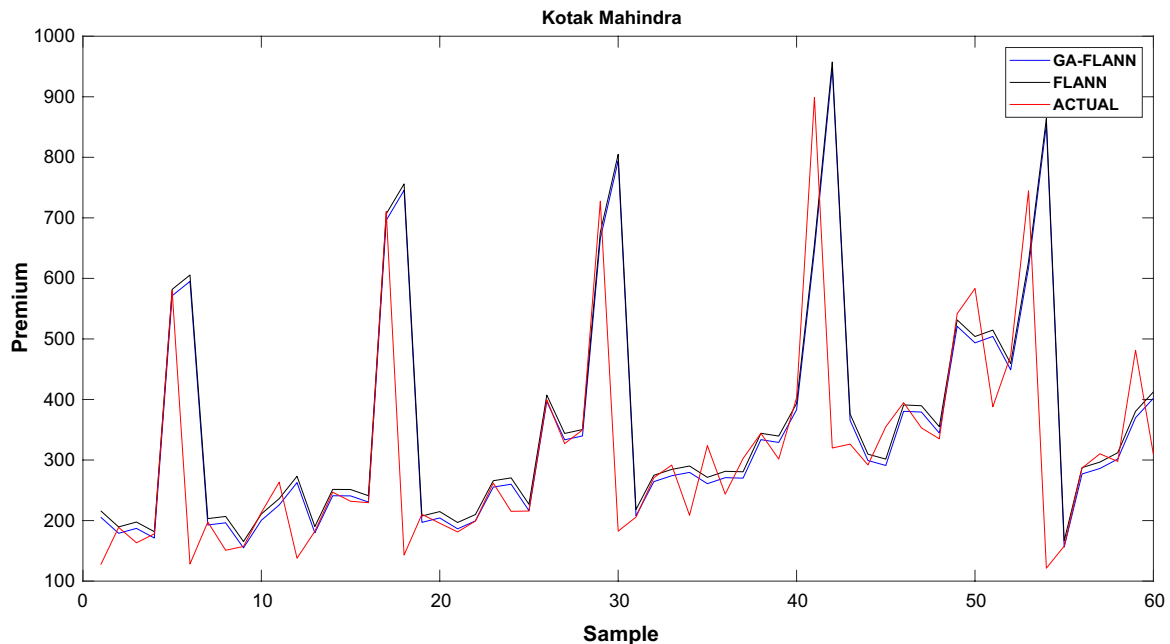


Fig. 16 Predictive result analysis of Kotak Mahindra Old Mutual

collection was quite appreciable. During this survey, period INR 684.64 crore was collected in January 2015, INR 460.62 crore in January 2016, INR 697.64 crore in January 2017, INR 976.91 crore in January 2018, INR 1421.04 crore in January 2019, and INR 1503.95 crore in January

2020 (Fig. 12). The business in the previous year was quite impressive except for April and May month as such the impact of coronavirus is a matter of concern.

ICICI Prudential is a leading life insurance company in India among 24 companies. The company has had a good

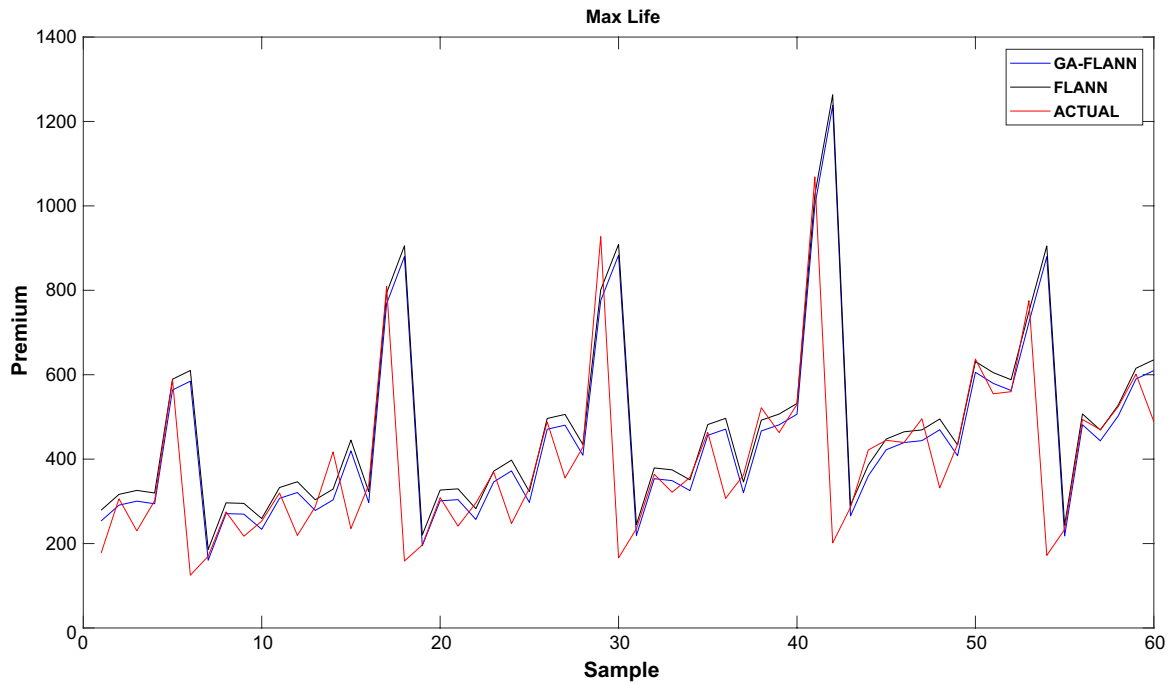


Fig. 17 Predictive result analysis of Max Life Insurance

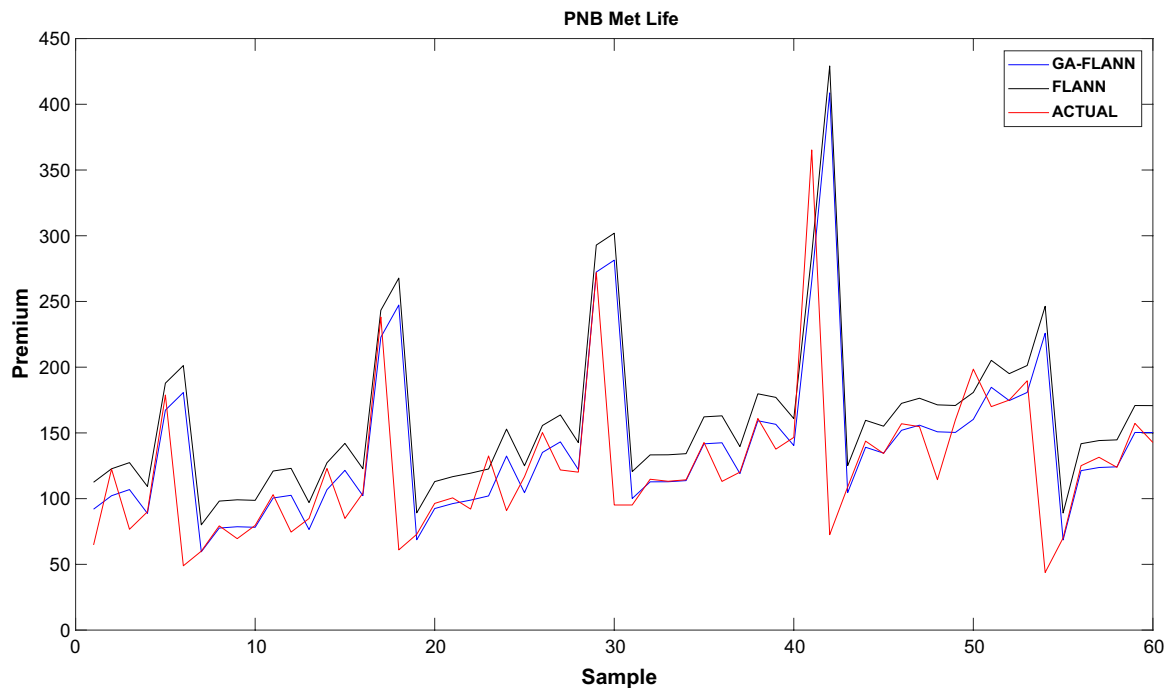


Fig. 18 Predictive result analysis of PNB Met life

start with INR 532.72 crore premium collection in January 2015, INR 559.33 crore in January 2016, INR 827.32 crore in January 2017, INR 863.28 crore in January 2018, INR 957.81 crore in January 2019, and INR 1112.32 crore

(Fig. 13). The business volume of premium collection was consistent throughout the survey period, but sluggish in the collection was observed in 2020 due to covid-19.

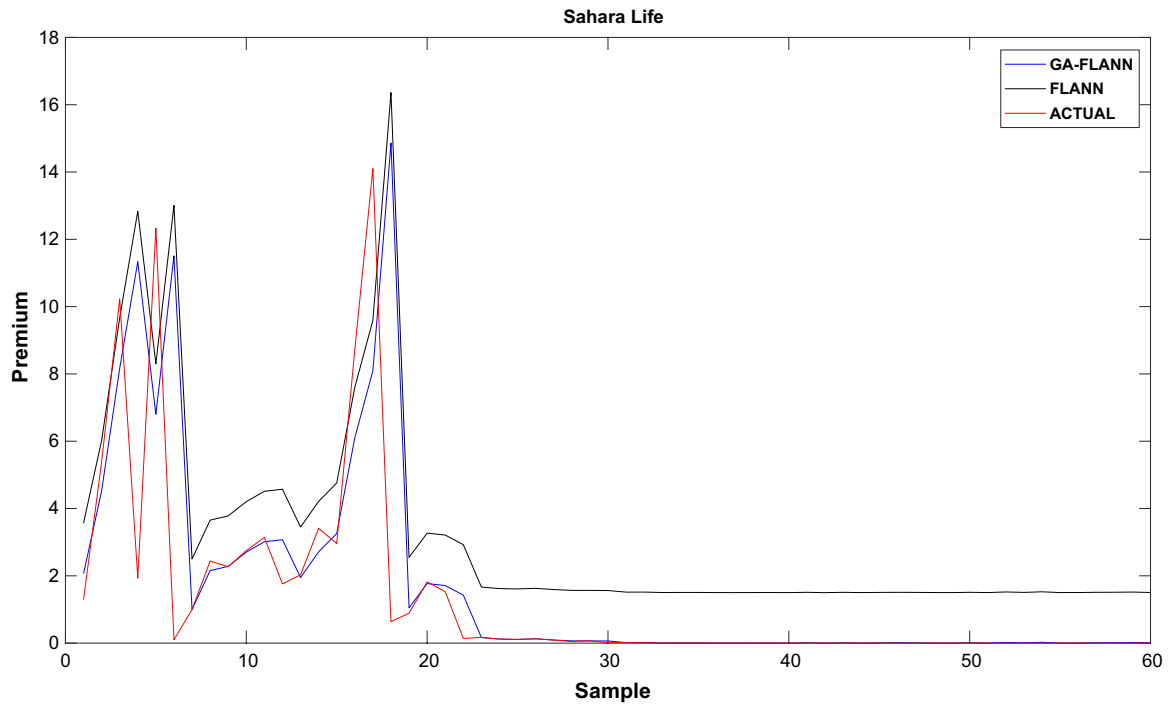


Fig. 19 Predictive result analysis of Sahara life

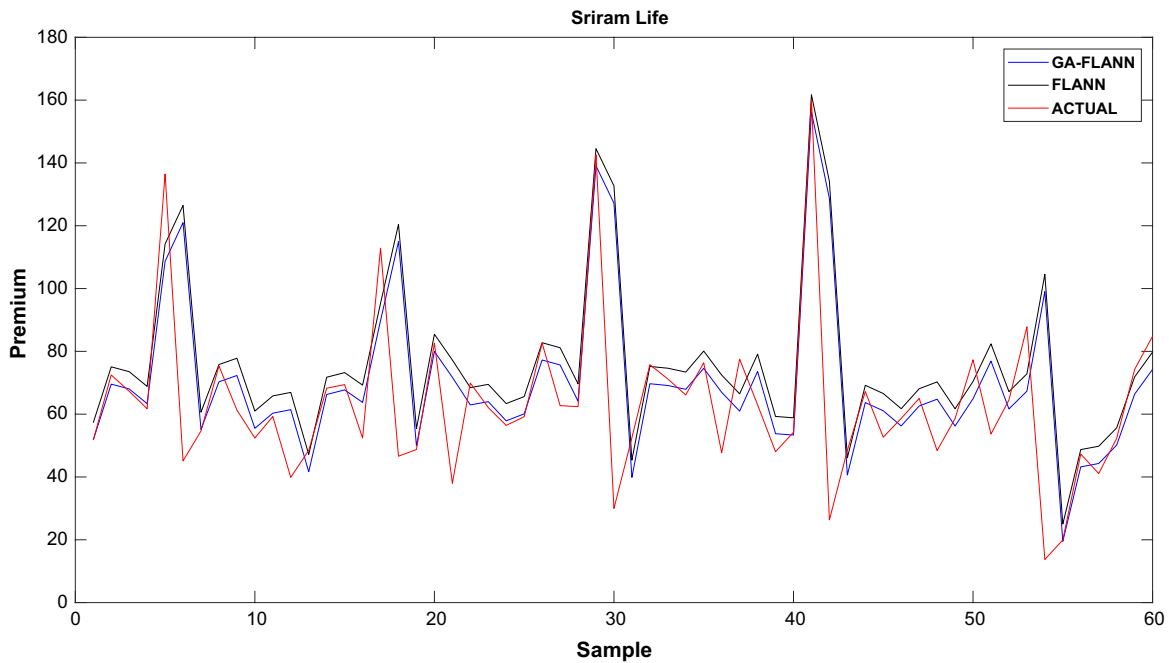


Fig. 20 Predictive result analysis of Sriram life

Birla Sun life is a premier life insurance company in India. The performance of this company was also impressive. According to the policies premium, it had a good start in January 2015 with INR 291.97 crore, following January

2016 to 2020. For July 2020, it was INR 504.04 crore, but the previous months of May and June were INR 261.75 and 150.69 crore (Fig. 14).

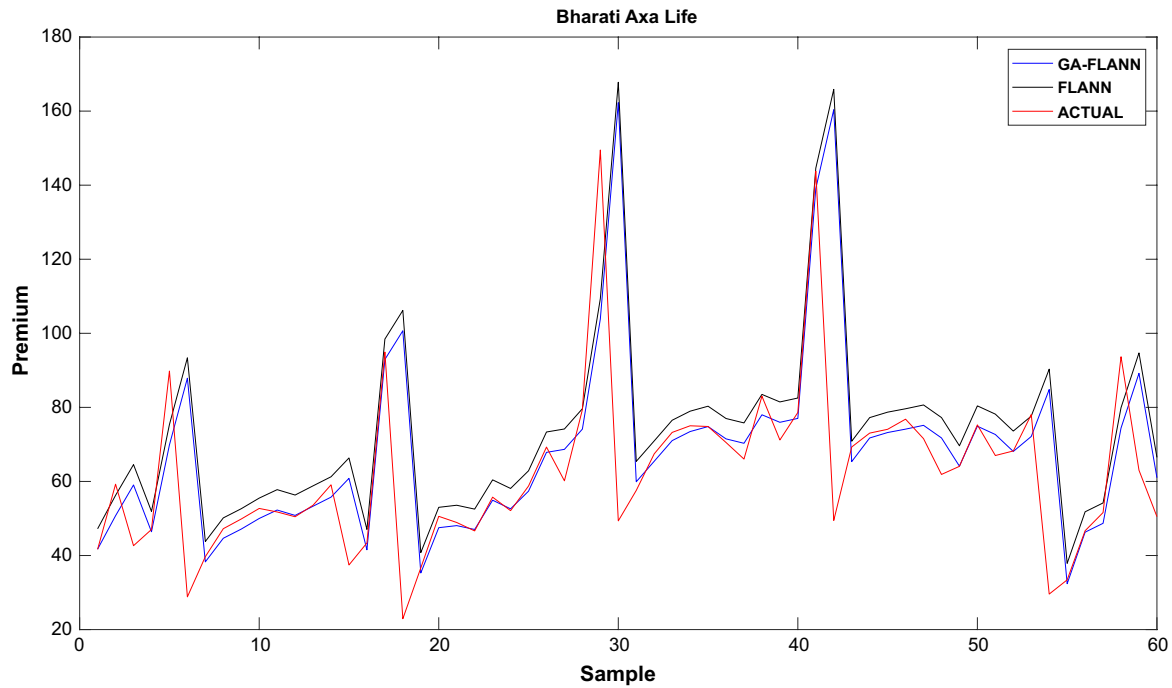


Fig. 21 Predictive result analysis of Bharati Axa life

Aviva life is sponsored by Dabur a leading pharmaceutical company. It has also a good position in the life insurance sector in India. Even though the company is quite famous, the premium collection was not impressive. In 2015 January, it collected only INR 36.75 crore and increased to INR 122.54 crore in April. Thereafter, the company has reached INR 100 crores (Fig. 15). It closed by INR 10.25 crore in December 2020 which has no consistent records of premium collection.

Kotak Mahindra Old Mutual is a leading life insurance company in India. It has gained a good position in the life insurance sector provided other banking and non-banking business. In January 2015, it collected the premium value of INR 139.24 crore, January 2016 INR 188.78 crore, January 2017 INR 246.83 crore, January 2018 INR 399.56 crore, January 2019 INR 344.11 crore, and January 2020 583.34 (Fig. 16). However, the policies premium for the year 2020 was damaged by covid-19 and suddenly fell to INR 310.18 in December 2020.

Max Life Insurance Company holds a good position in the Indian insurance market. The premium collection for January 2015 was INR 320.92 crore, January 2016 INR 306.15 crore, January 2017 INR 417.00 crore, January 2018 INR 488.26 crore, January 2019 INR 521.79 crore, and January 2020 INR 637.14 crore. The covid-19 effect was visible in May and June 2020 when it reduced premium collection to INR 171.84 and 233.57 crores (Fig. 17). Hence, it can be said that the lockdown affected the insurance market severely.

PNB Met life is also a leading insurance company that provides many types of products. The premium collection for January 2015 was INR 88.47 crore, January 2016 INR 122.45 crore, January 2017 INR 122.93 crore, January 2018 INR 150.24 crore, January 2019 INR 160.96 crore, and January 2020 INR 198.52 crore. The covid-19 effect was visible in May and June 2020 when it reduced premium collection to INR 70.08 and 125.06 crores (Fig. 18). Hence, it can be said that the lockdown affected the insurance market severely.

Sahara life is a partner of Sahara India Parivar. It has also a tremendous grip on the life insurance market. From January 2015 to July 2018, the premium collection was adequate but due to some reason, there was no evidence found for premium collection from August 2018. The data revealed that the premium collection was slowly declined and dropped to zero (Fig. 19).

Sriram life is a partner company of Sriram finance. This is also a leading insurance company according to its performance in premium collection. Initially, in January 2015, it collected INR 54.44 crore, and later in January 2016 INR 72.48 crore, January 2017 INR 68.26 crore, January 2018 INR 82.65 crore, January 2019 INR 62.98 crore, and January 2020 INR 77.32 crore. From the existing data, it can be observed that it has a consistent record in the premium collection but the effect of covid-19 was also seen in May and June 2020 (Fig. 20).

Bharati Axa life is an associate company of Airtel communication. It is also a leading insurance company in India

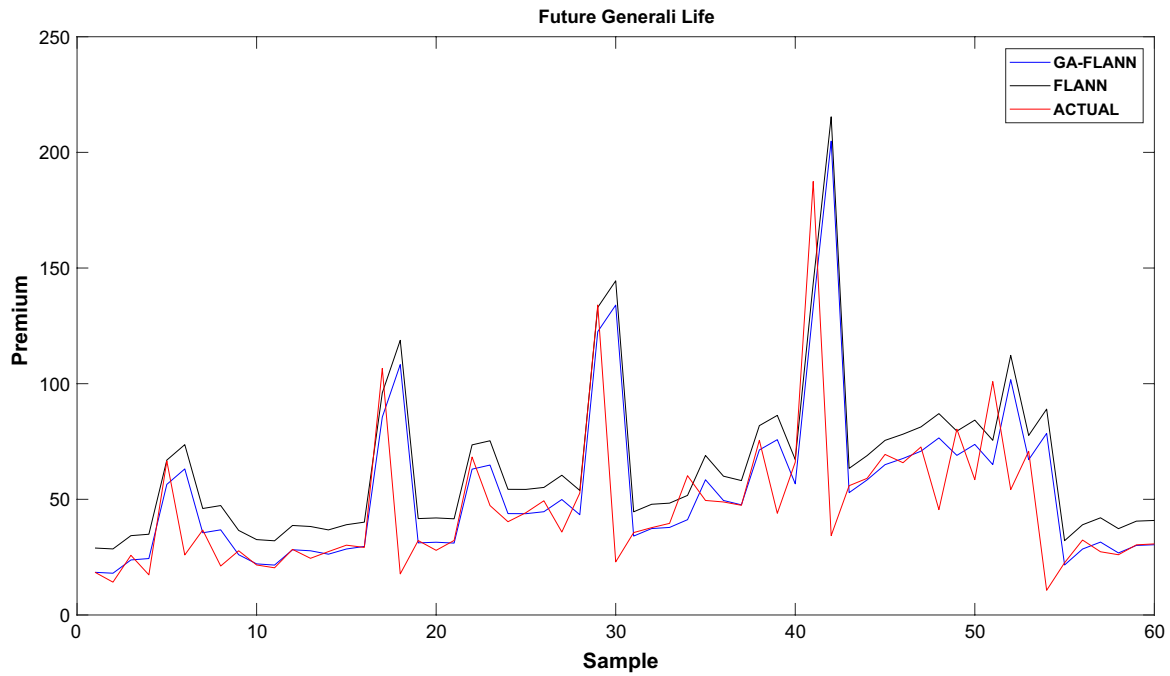


Fig. 22 Predictive result analysis of Future Generali Life

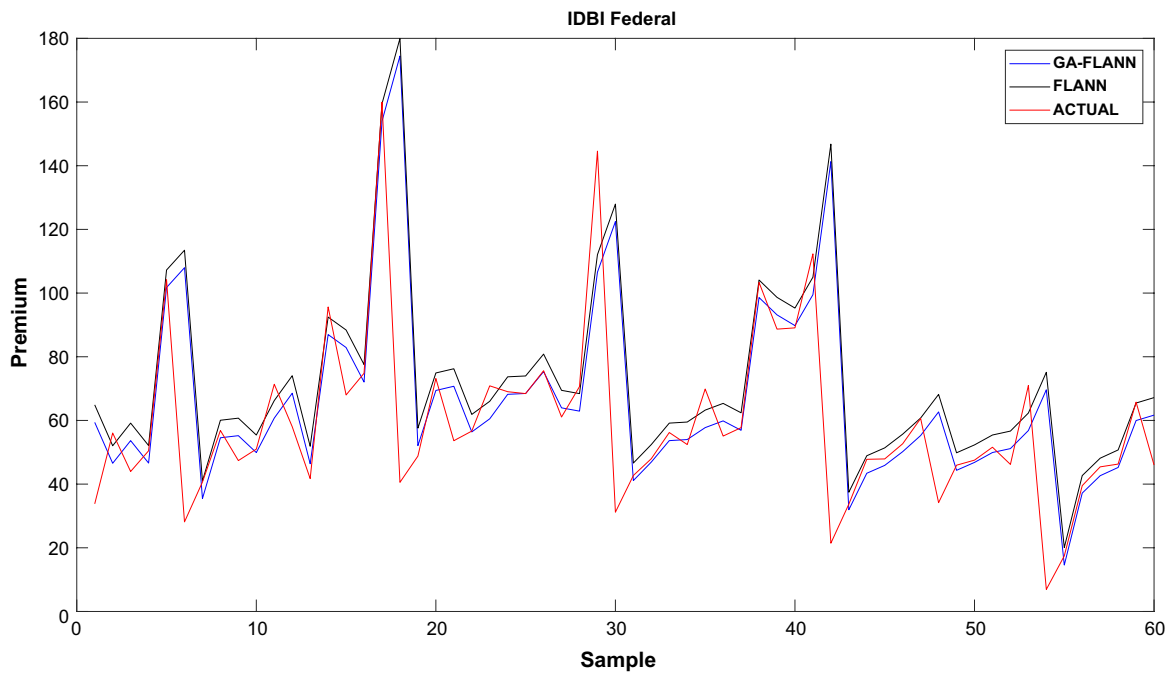


Fig. 23 Predictive result analysis of IDBI federal

that is doing good business in terms of varieties of products and customer awareness. Initially, in January 2015 it collected INR 46.74 crore, January 2016 INR 59.26 crore, January 2017 INR 59.09 crore, January 2018 INR 69.28 crore, January 2019 INR 83.02 crore, and January 2020 INR 75.27

crore. From the existing data, it can be observed that it has a consistent record in the premium collection but the effect of covid-19 was also seen in May and June 2020 worth INR 29.59 and 33.42 crores (Fig. 21).

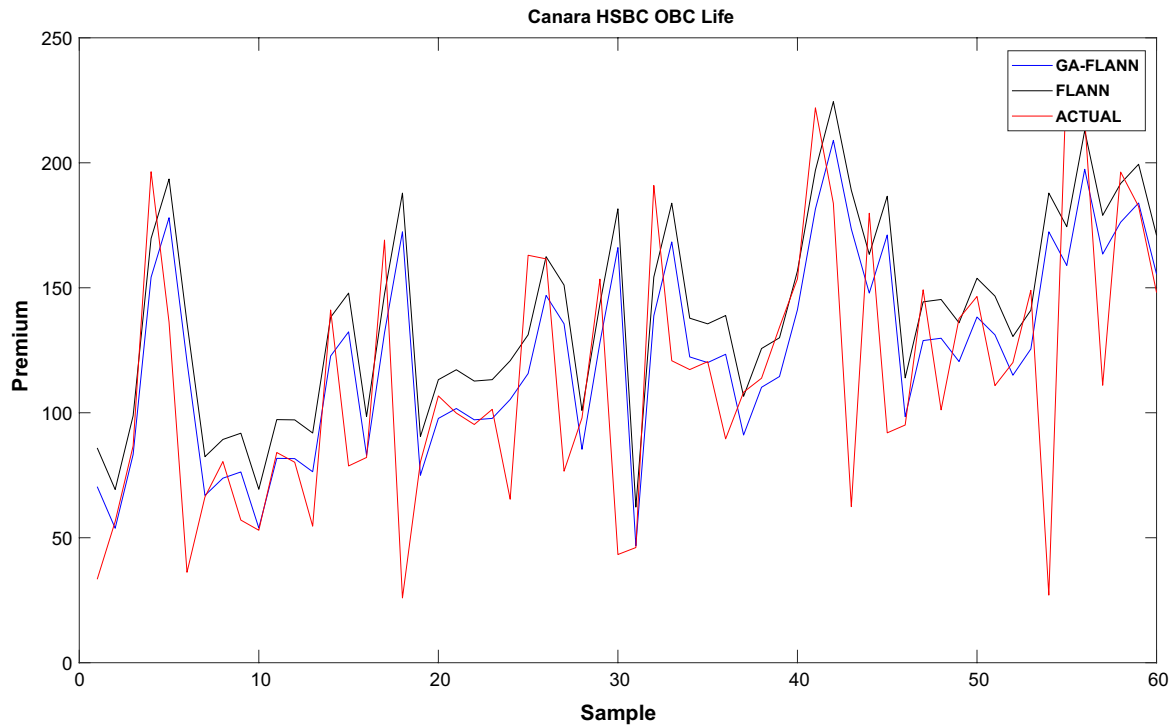


Fig. 24 Predictive result analysis of Canara HSBC OBC life

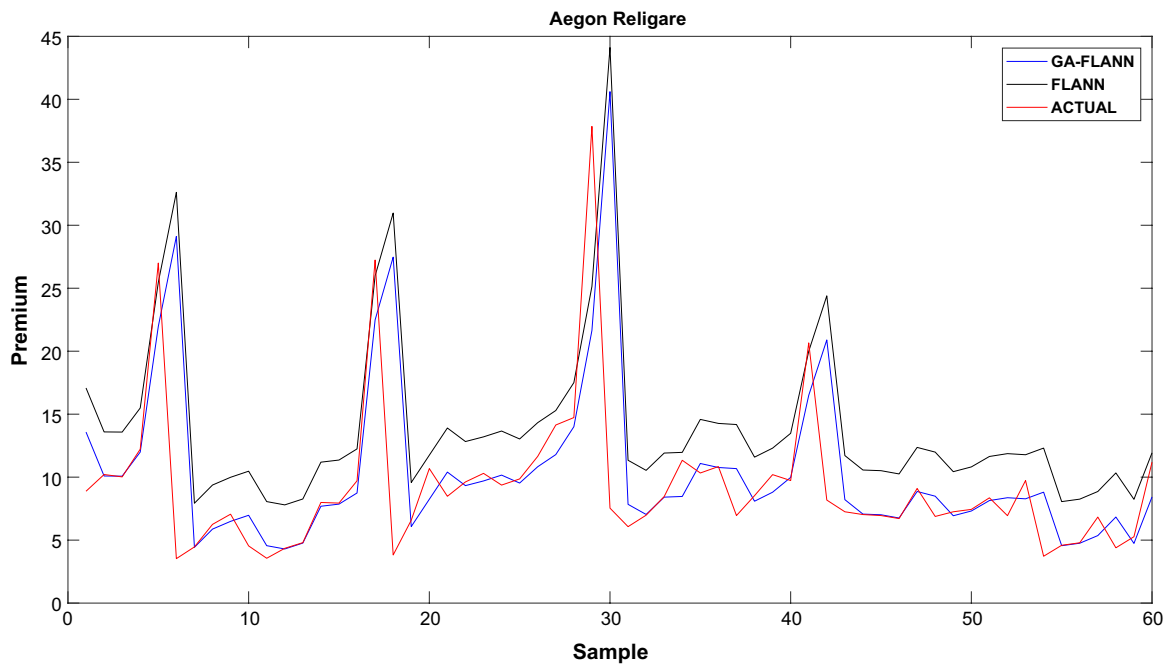


Fig. 25 Predictive result analysis of Aegon Religare

Future Generali Life is a premier life insurance company in India. It had a consistent record of the premium collection since 2015. Initially, in January 2015 it collected INR

32.15 crore, January 2016 INR 14.19 crore, January 2017 INR 27.40 crore, January 2018 INR 49.38 crore, January 2019 INR 75.52 crore, and January 2020 INR 58.50 crore

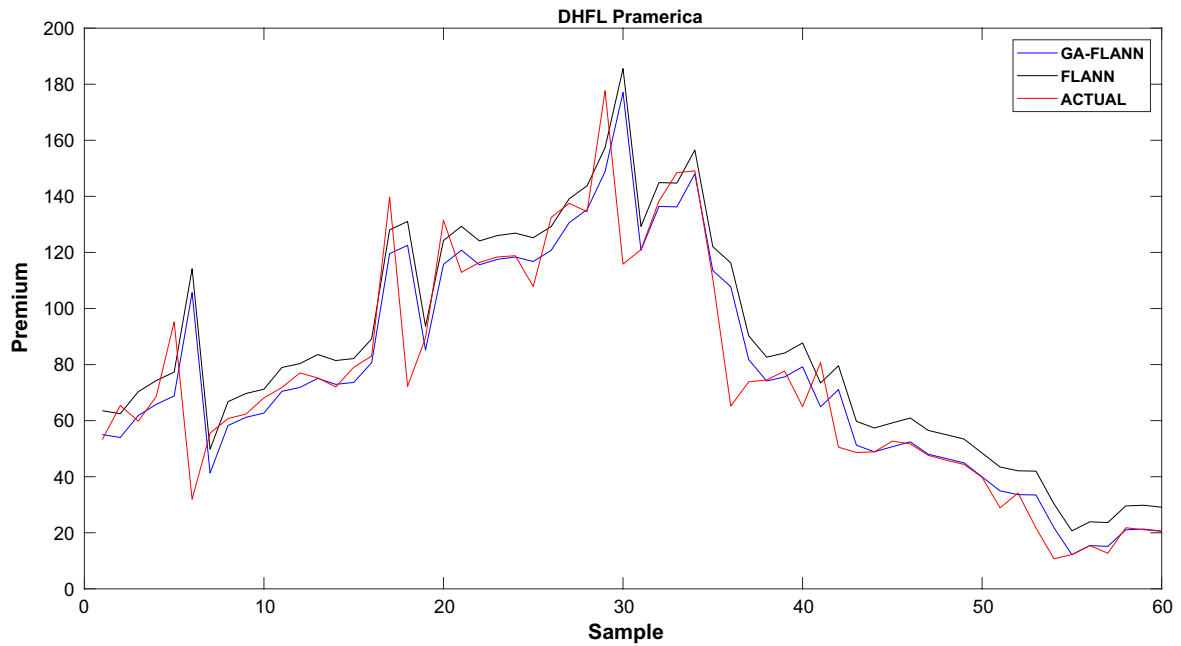


Fig. 26 Predictive result analysis of DHFL Pramerica

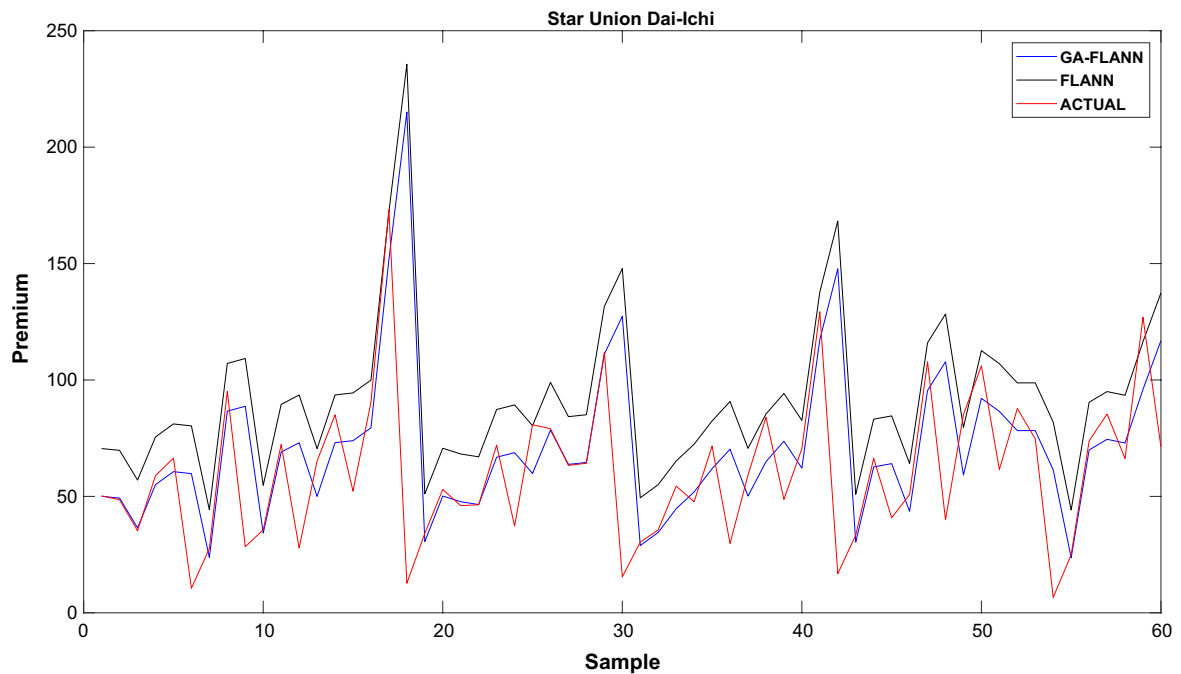


Fig. 27 Predictive result analysis of Star Union Dai Ichi

(Fig. 22). From the existing data, it can be observed that it has a consistent record in the premium collection but the effect of covid-19 is also seen in the entire year 2020.

IDBI federal is a leading insurance company of IDBI Bank. The policies premium collection for January 2015 was INR 53.52 crore, January 2016 INR 56.05 crore, January

2017 INR 95.65 crore, January 2018 INR 75.61 crore, January 2019 103.35, and January 2020 INR 47.53 crore. Sometimes the premium collection crossed INR 100 crore, but due to covid-19, only INR 6.92 crore was collected in May 2020 (Fig. 23).

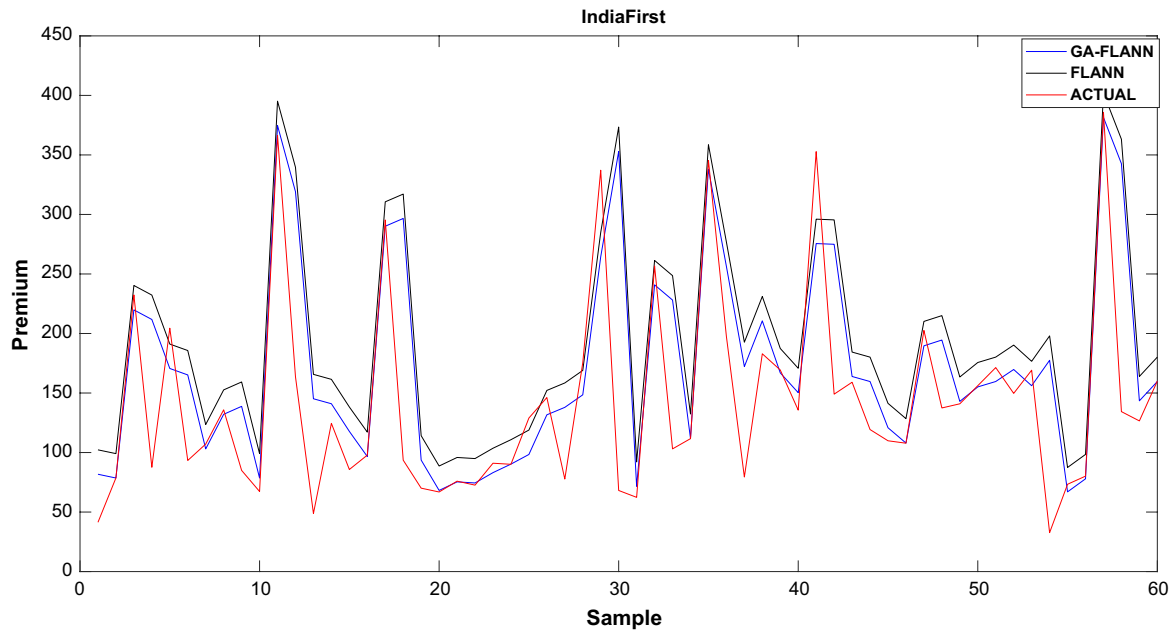


Fig. 28 Predictive result analysis of India first

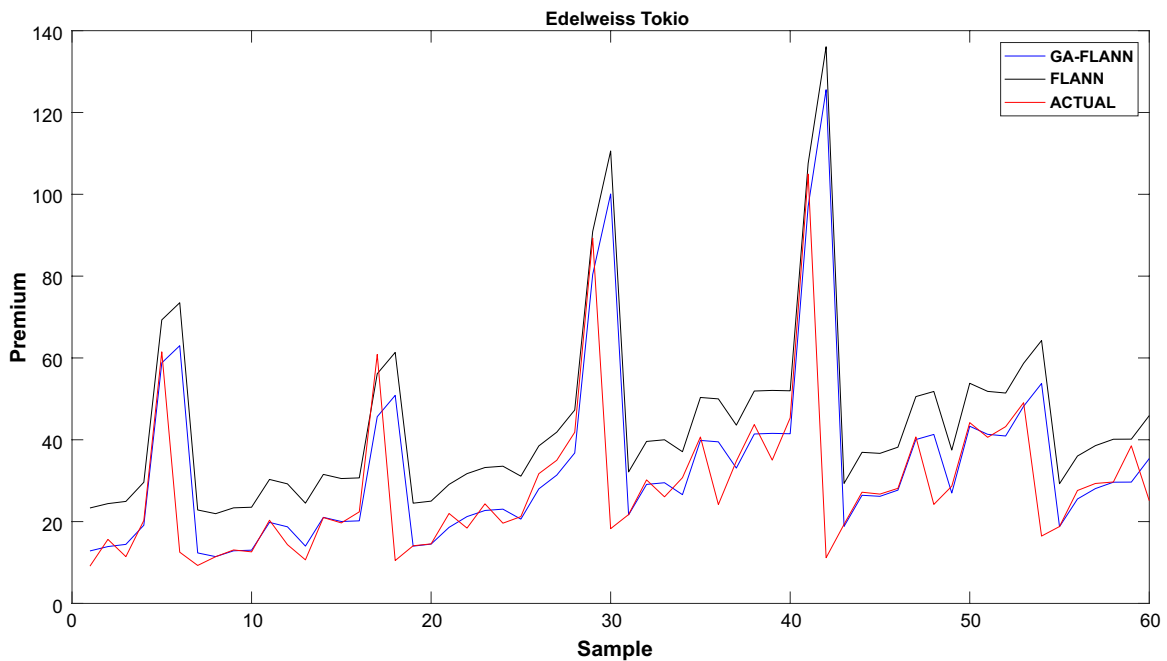


Fig. 29 Predictive result analysis of Edelweiss Tokio

Canara HSBC OBC life is a leading insurance company in India that offers many varieties of insurance products. The premium collections of this company have no consistency in the survey period. Sometimes the premium collection was more than INR 100 crore, further less than INR 30 crore also.

The entire period of 2020 has good business altogether, but in May, it was INR 27.05 crore (Fig. 24).

Aegon Religare provides all kinds of insurance products to Indian citizens. It has not succeeded like other companies. The premium collection was not seen as more than two digits. Sometimes even it is lower than one-digit revenue also.

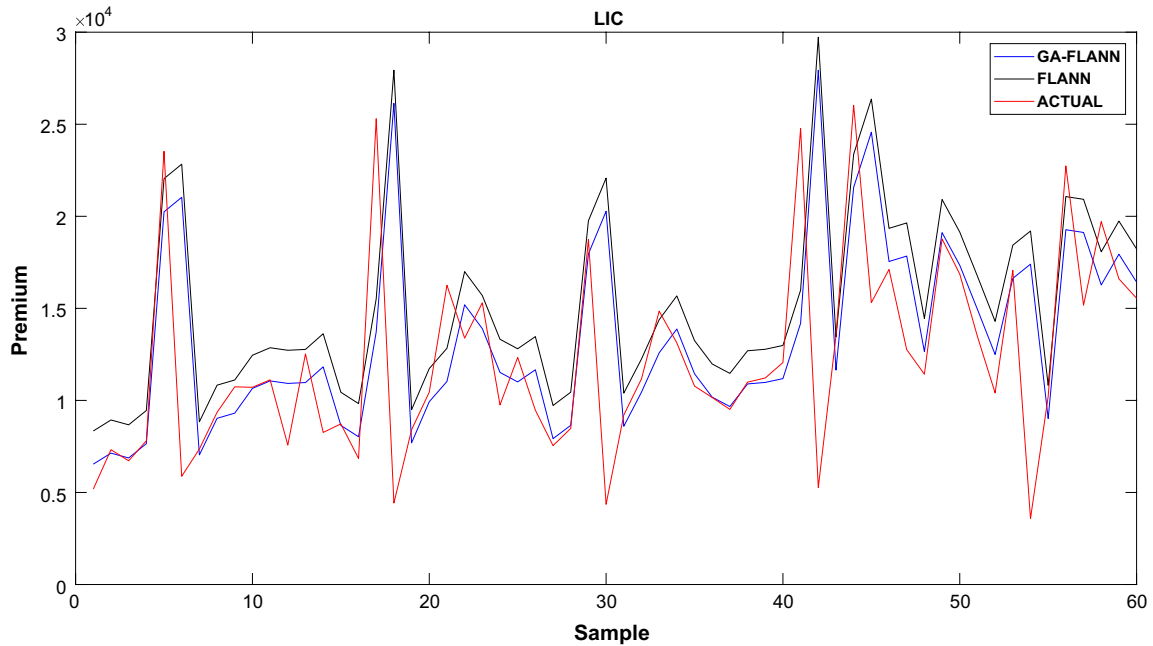


Fig. 30 Predictive result analysis of Life Insurance Corporation

The COVID-19 has affected this company severely which can be observed for May and June 2020 worth INR 3.72 and 4.59 crore (Fig. 25).

DHFL Pramerica is also a leading insurance company in India. The premium collection for January 2015 was INR 62.24 crore, January 2016 INR 65.40 crore, January 2017 INR 72.03 crore, January 2018 INR 132.47 crore, January 2019 INR 74.48 crore, and January 2020 INR 39.76 crore (Fig. 26). The COVID-19 effect was visible in March, April, May, and June 2020 where it reduced premium collection. Hence it can be said that the lockdown affected the insurance market severely.

Star Union Dai Ichi is also a leading insurance company in India. The premium collection for January 2015 was INR 78.75 crore, January 2016 INR 48.55 crore, January 2017 INR 85.02 crore, January 2018 INR 79.08 crore, January 2019 INR 83.98 crore, and January 2020 INR 106.08 crore. The COVID-19 effect was visible in May 2020 when it reduced premium collection to INR 6.61 crore (Fig. 27). Hence it can be said that the lockdown affected the insurance market severely.

In January 2015, India first has had a good start of premium collection about INR 244.01 crore and suddenly reduced to INR 78.66 crore in January 2016. In January 2017, it increases its premium INR 124.52 crore and again it gained to INR 146.18 crore in January 2018 (Fig. 28). In January 2019, it collected INR 182.95 crore and slump down its premium to INR 156.15 crore in January 2020; however, in August 2020 it collected around INR 385.87 crore

premiums, and thereafter the premium collection declined due to lockdown.

Edelweiss Tokio is also a leading insurance company in India. According to the existing data, this company represents a poor performer in the insurance premier collection. Sometimes this company even not made double-digit premium collections. From the data, it is evident that covid-19 has affected the premium collection (Fig. 29).

Life Insurance Corporation of India is a leading insurance company in India. It is directly monitored and controlled by the government. The company is widely spread across the country. From the data, it revealed that it had a good move in premium collection. The premium collection for January 2015 was INR 5858.55 crore, January 2016 INR 7323.67 crore, January 2017 INR 8261.31 crore, January 2018 INR 9469.07 crore, January 2019 INR 10,992.15 crore, and January 2020 INR 16,861.98 (Fig. 30). However, the year 2020 was affected by the business hugely. Particularly in May 2020, the premium collection was INR 3581.65 crore.

Discussion

The World Health Organization declared the Covid-19 as a world pandemic on March 11, 2020. The spread of SARS-CoV-2 coronavirus made the circumstance panic. People fear to travel, transact, and interact due to the severe spread of coronavirus across the world. Consumers' habits have changed from optimistic to pessimistic. Now they feel insecure about their health rather than wealth. Under

the prevailed furious circumstances, the governments have undertaken several steps on health measures like social distancing, sanitization, and consciousness among the people. When the first case was identified on January 30, 2020 in India, the government declared three phases of lockdown in the entire country. Just after the lockdown, the economy of the country was severely affected in all sectors. Prolong lock-down changed the psychology of individuals. The fear of survival forced individuals to protect themselves from this epidemic. Among all the sectors, life insurance has a major industrial revolution to counter the pandemic and could provide self and family protection. In this crisis, predicting the future demand for life insurance products is the important facet of this observation. The study has extended its prediction on 24 life insurance companies in India where monthly premium collection data analyzed through FLANN (Functional Link Artificial Neural Network) techniques. The results exhibited for 65 months of the premium collection from January 2015 to December 2020.

The predictive analysis says that Bajaj Allianz Life Insurance has initially collected INR 274.67 crore premium value in January 2015, thereafter increasing its premium to INR 1182.11 crore in April 2019 with an average of INR 361.54 crore. Since May 2019, it reduced its premium collection as a result of this pandemic. However, the prediction exhibited that the premium collection could be increased in the new normal. In the beginning, Exide life received INR 77.26 crore in January 2015 and gradually increased its premium collection in the next preceding months. It received almost INR 162.52 crore in April 2020 with an average of INR 66.20 crore, and thereafter, it slashed its premium collection. Reliance life received lucrative premium value since January 2015 with an average of INR 95.15 crore in 65 months of data. Since April 2020, it observed that there is a fall in premium collection. SBI Life is the subsidized insurance company of SBI which received an average premium value of INR 1088.93 crore in the entire survey period. However, since January 2020 it reduced the premium collection. Tata AIG has initially collected INR 23.91 crore premium value in January 2015, thereafter increasing its premium to INR 596.44 crore in April 2019 with an average of INR 172.49 crore. Since April 2019, it reduced its premium collection as a result of this pandemic. HDFC standard life has initially collected INR 684.64 crore premium value in January 2015, thereafter increasing its premium to INR 2551.61 crore in April 2019 with an average of INR 1084.26 crore. Since April 2019, it reduced its premium collection as a result of this pandemic. ICICI Prudential is a sister concern company of ICICI Bank which received an average of INR 797.45 crore premiums in the entire survey period. But it slashed down premium value since March 2020. Birla sun life is a sister concerned company of Birla group which received an average of INR 273.58 crore premiums in the entire survey

period. But it slashed down premium value since April 2020. Aviva life has collected an average premium value of INR 23.93 crore which signified as a poor performer. Srilam life, Bharati Axa life, Future Generali, IDBI federal, Kotak Mahindra old mutual, Max life, DHFL Pramerica, Star Union Dai-Ichi, IndiaFirst, Edelweiss Tokio, and PNB met life have also reduced their premium collection since April 2020. Among all the companies, Sahara life has not received any position since August 2018. But Canara HSBC improved its performance in December 2020. Aegon Religare has an average premium value of INR 10.13 crore which least among all the companies. LIC is a premier insurance company in India which has collected INR 5858.55 crore in January 2015. Sometimes it increased the premium collection and reached INR 26,030.16 crore in July 2020. But it is observed the zigzag movement in the entire survey period which may have a pandemic effect. In this analysis, consumer psychology is the key variable where premium collection depends on the entire period of 11 months closed the various business segments, the insurance industry also got affected.

Conclusion

Covid-19 has altered the business and economy with unexpected changes never before. It transformed the business from physical transactions to social distancing, isolation, and virtual structure. Now life protection is becoming a major concern among individual consumers. With this uncertain impact on well-laid plans, financial or otherwise, insurance is emerging as one of the ways to financially protect themselves and their families. The spread of disease vividly changed the psycho-physiological behavior of consumers on their purchase intention. The perception of financial gain and risk associated with this disease has confused them to selecting an appropriate insurance plan that could protect their lives. This critical situation pushes consumer behavior in a different direction. Either the consumer takes a rational or emotional decision to fulfill its desire. Though investment in life insurance could be an important factor for pre-survival death benefits, intelligent consumers considered it as economic mileage for the future. In this regard, a better understanding between the consumers and the insurance companies is vital to building loyalty to insurance products. Insurance companies should familiarize themselves with all the positive and negative impacts of their brand to identify the need and expectations of the consumers. Thereby the insurance companies could understand the behavior of the consumer toward insurance products even in this crisis. As most of the statistical methods fail to determine the exact prediction, the study has considered higher-order neural network techniques for the future growth of insurance premium

value. In this article, an intelligent-based higher-order functional link neural network is proposed to analyze and predict consumer behavior toward the health insurance policy. For effective performance of the proposed neural network, a genetic algorithm has been used to optimize the parameters and the simulation results of the proposed model are found as a suitable prediction model than other competitive machine learning approaches. The study critically examined the purchase intention of the consumers toward 24 life insurance companies in the Indian sub-continent where most of the companies fail to receive the good value of premium from April 2019. To identify the loopholes of marketing strategies, the researcher measured a predictive analysis on 65 months of available data and predicted future growth. The observation indicated the partial movements in the premium collection were affected by several causes before this pandemic. The consumers may be unaware of the benefits or the companies are failed to understand the behavior. However, the Covid-19 effect has a less significant role in the downfall of their premium collection.

The study is confined only to 24 life insurance companies in India for a specific period of 65 months. The Covid-19 effect may not be considering the behavior of consumers' on purchase of any insurance product. The consumers' behavior may change according to the need and expectation, so it is needed to focus on various behavioral aspects of the consumer. As per the source, life-threatening could be an important factor for insurance products where the consumers may select or dispose of the insurance product for the safety and security of their lives. Moreover, the present study has not considered other computational techniques such as deep learning or data mining. Hence, such kind of prediction analysis can be done with the help of deep learning algorithms. In the future, the study can be extended for another financial forecasting such as credit card user behavior, mobile banking, or purchase intensity of bonds. The study can also be expanded to other insurance premium forecastings such as agriculture and crop protection insurance and fire and safety insurance.

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Declarations

Conflict of interest The authors declare that this manuscript has no competing interest with any other published source and has not been published previously (partly or in full). No data have been fabricated or manipulated to support the conclusions.

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