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AN INTELLIGENT RISK ASSESSMENT MODEL FOR TRADING IN THE INDIAN GOLD MARKET

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Abstract:

Gold is considered an important form of investment as love for the yellow metal has lured the people for centuries, especially in India and China which together account for more than half of the world's total gold demand. The gold market, like the equity market is also subject to volatility. Hence, accurate forecasting of the Value at Risk (VaR) for gold is of vital importance. This study explores the possibility of exploiting the benefits of Artificial Neural Networks and Nature Inspired Algorithms for forecasting purposes and solving optimization problems of complex nature respectively to forecast the VaR values of the Indian gold market using the conventional VaR methods. Historical Indian gold price data of 1985 observations covering the period from January 1, 2009 to March 31, 2017 has been used for the study. This paper proposes an innovative combination model of the conventional VAR method (Historical Simulation) and a hybrid of Nature Inspired Algorithm (Invasive Weed Optimization) and Artificial Neural Network (Feed Forward Back Propagation), for forecasting the VaR values of the Indian gold market. The accuracy of the model in forecasting the VaR values has been tested successfully using the back testing methods. The proposed model has been found to be an effective and efficient VaR forecasting model.

Key Words: Back testing, Combination model, Historical simulation, Indian gold market, Value at risk.

1. Introduction:

The love for gold in Indians is acknowledged worldwide. Gold is considered to be a significant part of the Indian household as it is considered an auspicious metal that is symbolic of good fortune, prosperity, affluence and purity. The Indians spend a considerable amount of their savings on purchasing gold as it is forms a vital part of all Indian rituals, festivities and celebrations. A major portion of the budget of Indian marriages is spent on buying gold. It is also considered as a safe form of investment. Hence, the Indians invest substantially in gold. Consequently, India is the second largest consumer of gold in the world (India Gold Policy Centre, 2017). Thus, precise prior prediction of prices of gold would immensely help the investors and the other stakeholders in investing intelligently. The study is significant in the context that it proposes a model that can precisely evaluate the risk of investing in Indian gold market by predicting its Value at Risk (VaR) value.

The paper is divided into Sections 1 to 5. Section 1 introduces the research problem and the associated methods of VaR, Invasive Weed Optimization Method, Artificial Neural Networks and back testing methods used for the study. Section 2 discusses the previous research done in the area through a literature survey. The data considered for the study and the methodology followed to solve the research problem are discussed in Section 3. The results obtained are listed in Section 4 while Section 5 discusses the conclusions drawn from the study.

Value at Risk (VaR): VaR has become the most extensively accepted tool to quantity market risk. VaR is the extreme value of loss that an asset can undergo at a specific probability in a given time period. (Morales, 2005) defined VaR as the quantile of the given distribution of return values. There are three conventional VAR methods of calculating risk. These are: Variance-Covariance (VCV) method, Historical Simulation (HS) method and Monte Carlo (MC) Simulation method.

Variance-Covariance (VCV) Method: (Morgan, 1996) introduced the Rikmetrics method. This comprised of an extensive database of estimated variances as well as the co-variances of the asset return values which were used for the VaR calculations (Guermat and Harris, 2002). This method led to the popularity of the Variance-Co-variance approach for VaR computations. This method is based on the assumption that the return values are normally distributed. The VaR values in this method are a function of the values of the standard deviation at the specified level of confidence. The values of standard deviation are computed from the return values data.

Historical Simulation (HS) Method: This is a non-parametric method of estimation of VaR. Unlike the Variance-Co-Variance method, it does not assume any kind of functional distribution for the return value data. The historical data is used to determine the future VaR values. It is based on the premise that the historical pattern of the return values in the past is suggestive of the trends of the returns in the future. This method makes lesser number of assumptions regarding the factors affecting the return values. Instead, it generates a hypothetical set of data by applying the historical fluctuations in market prices to the existing prices. The data is thereafter sorted according to the values of profits/losses. VaR value is then computed as the value that is greater than or equal to the requisite percentage of times.

Monte Carlo Simulation (MC) Method: Monte Carlo Simulation method does not make any assumption about the return values following normal distribution and instead uses the actual return historical data distribution for computing the VaR values. The returns are calculated by executing multiple instances of the simulation runs. Simulated returns are initially generated from a sampled probability data distribution. These return values are then sorted as per their magnitude. These are then used to compute the VaR values at the desired level of confidence. Since this method works for all probability data distributions, it is considered to be a flexible VaR computation technique. The computational overhead rises with the increase in size of dataset under consideration.

Invasive Weed Optimization Algorithm: Mehrabian and Lucas (2006) proposed the Invasive Weed Optimization (IWO) algorithm to solve complex optimization problems. It is a nature inspired algorithm and is based on the invasive inhabitation behavior of the weeds. This algorithm proceeds with spreading initially a finite number of weeds in a random manner across a search space of dimension n. New weeds are produced by the weeds with high fitness value and are again spread randomly across the search space. The newly produced weeds further produce new weeds depending upon their fitness and this cycle of reproduction goes on till a maximum value for the number of weeds is reached. Thus, in each cycle, following the principle of survival of the fittest, the fittest weeds survive and reproduce, while the rest are abolished. The IWO algorithm imitates this behavior of the weeds and involves execution of several iterative cycles which continue till a maximum optimized solution has been obtained or till maximum limit for the number of iterations has been reached.

Artificial Neural Networks: ANN is an artificial intelligence technique that imitates the behavior and working of brain of the human being. Hecht-Nielsen (1990), Maren et.al (1990), Zurada (1992), Fausett (1994), Ripley (1996) besides others described the structure and operation of the ANNs in their studies. These networks learn from examples. These networks establish relationship between the input and output variables by suitably adjusting the network weights. One of the major advantages of the ANNs over the statistical and empirical methods is their ability to model complex problems as these networks do not require any prior information about the type of relationship between the model variables (Hubick, 1992).A number of different architectural models of ANNs are available. This paper considers Feed Forward Back Propagation Artificial Neural Network (FFBP ANN) model for hybridization with the IWO model for prediction of Indian gold prices. The FFBP type of neural network has three types of layers-input, hidden and output layer. All the neurons in a layer are connected to every neuron of the succeeding layer. The network is trained using the Back propagation learning algorithm. The output obtained is a function of the current values of the inputs and the weights. The value of error computed as difference between the forecasted and the actual values is propagated backward in the network to update and adjust the network weights.

Back Testing Methods: Back testing methods are tools used to validate the accuracy and adequacy of the VaR models. The general methodology followed by the back testing methods is to compute over a historical time period, the number of times the actual loss exceeds the predicted VaR value. This count of exceedances is then compared to a pre-specified level. A number of back testing methods have been proposed from time to time. This paper, however, considers the following three methods for validating the proposed VaR model. These are: Kupiec Test, Christoffersen Test and the Joint Test.

a. Kupiec Test: The Kupiec test is also called the Proportion of Failure (POF) test. It is an unconditional coverage test to check the validity of a VaR model by checking whether the count of exceedances lies within the predefined VaR level (Kupiec, 1995). Thus, mathematically, it can be stated as:

$$H_t = \begin{cases} 1 & if\ Yt < Qt \\ 0 & if\ Yt \geq Qt \end{cases}$$

Assuming the Null hypothesis to be true, the test statistic is

$$-2\ln\left(LR_{uc}\right) = -2\left[n_0 \ln\left(1-\pi_{\exp}\right) + n_1 \ln\left(\pi_{\exp}\right) - n_0 \ln\left(1-\pi_{\text{obs}}\right) - n_1 \ln\left(\pi_{\text{obs}}\right)\right] \sim \chi_1^2$$

Where n_1 denotes the count of violations when the count of exceedances surpass the pre-defined VaR level; n_0 denotes the number of acceptances when the pre-specified VaR levels are not violated; π_{exp} symbolizes the expected ratio of exceedances and π_{obs} denotes the actual number of exceedances and is computed as $\pi_{obs} = n_1 / (n_0 + n_1)$.

b. Christoffersen Test: Kupiec POF unconditional coverage test is unable to detect clustering of exceedances or violations. Christoffersen's test has been designed to test the independence of VaR violations. This test checks whether on a given day, the probability of exceedances of VaR is dependent on the previous day outcomes (Christoffersen, 1998). As per this test, for a model to be accepted, the VaR violations on a particular day should not be dependent on occurrences of violations on previous day (Jorion, 2007). The test statistic for exception independence can be expressed as a Likelihood ratio (LR_{ind}) which can be stated as:

$$LR_{ind} = -2ln[(1-\pi)^{(t_{00}+t_{10})}\,\pi^{(t_{01}+t_{11})}] + 2ln[(1-\pi_0)^{t_{00}}\,\pi_0^{t_{01}}\,(1-\pi_1)^{t_{10}}\,\pi_1^{t_{11}}].$$

Where $\pi_0 = t_{01} / (t_{00}+t_{01})$, $\pi_1 = t_{11} / (t_{10}+t_{11})$, $\pi = (t_{01}+t_{11}) / (t_{00}+t_{01}+t_{10}+t_{11})$

Further, t_{00}, t_{01}, t_{10}, t_{11} are computed using an indicator I defined as follows:

$$I = \begin{cases} 0 \text{ if VaR is not violated} \\ 1 \text{ if VaR is violated} \end{cases}$$

Here, t_{00} denotes the number of days when the violation neither occurs on a given day nor on the previous day; t_{01} is the count of the number of days when a no violation day is followed by a day when a violation occurs; t_{10} is the number of occurrences when a violation on a given day is followed by a day when no violation occurs; t_{11}denotes the count of occurrences when a violation on a particular day is followed by another violation on the successive day.

c. Joint Test: The Joint Test, also called the Christoffersen's Interval Forecast test was proposed by Christoffersen in 1998. It is a conditional coverage test that takes into account both the independence as well as the unconditional coverage properties. As such, it helps in the detection of VaRs which lack in either of the two properties (Campbell, 2005). The conditional coverage test statistic using both LR_{pof} test statistic of Kupiec and LR_{ind} test statistic of Christoffersen can then be stated as:

$$LR_{cc} = LR_{pof} + LR_{ind}$$

2. Literature Survey:

Accurate VaR measurement plays a vital role in countries with developed economies as well as in countries with developing economies. This is so because of the increasing interest of the developed countries to invest in the markets of the developing countries which requires prior accurate market risk assessment. The markets in the developing countries are generally more volatile as they are more sensitive to the external and internal shocks (Miletic & Miletic, 2013). Hence computation of VaR in such cases with the standardized VaR methods which work under the assumption of a normal distribution becomes even a more formidable task (Zikovic and Aktan, 2009). While there is substantial amount of literature on estimation of market Value at Risk of the developed countries, limited literature on estimation of VaR of the financial markets of the developing economies exists. Da Silva et al (2003) studied stock markets of ten Asian countries to estimate VaR using the Extreme value theory. Gencay and Selcuk (2004) used the stock prices time series data of nine developing economies across the world to study the performance of various VaR models. Bao et al (2006) evaluated and compared the VaR forecasts of five developing economies on the basis of probability of empirical coverage and the quantile loss suffered by these countries during the 2008-09 financial crisis. Zikovic (2007) evaluated the VaR models using stock indexes from the new member states of EU and concluded that the return series of the member states are heteroskdastic and variable, have fat tails and are auto correlated. Hence, he concluded that the VaR models for developed economies cannot be applied to the new member states. Zikovic and Aktan (2009) compared the performance of the VaR models using the stock return series of Croatia and Turkey. They concluded that the EVT model over-predicted risk and recommended use of Hybrid Historical Simulation model for risk estimation. Andjelic et al (2010) compared the Historical Simulation model and the Delta Normal VaR method for stock return of Slovenia, Serbia and Croatia. The Historical Simulation method was found to perform better at 99% confidence level. Nikolic-Djoric and Djoric (2011) used stock returns of Belgrade based on Student's t distribution and the Normal distribution to compute VaR of Belgrade and concluded that selection of an efficient volatility model is essential for accurate estimation of VaR. Bucevska (2012) studied the VaR of the financial markets of Macedonia and computed VaR using various GARCH models and concluded that VaR estimation was highly related to the choice of appropriate GARCH model. Barjaktaroviy et al (2014) evaluated the performance of the VaR models on the indexes of the emerging stock markets of Europe and concluded that the stock market characteristics along with the return series attributes, the considered confidence levels and the forecasting horizon are the major determinants of the efficiency of the VaR model for a particular market. Miletic and Miletic (2015) studied the VaR for stock returns of Czechoslovakia, Hungary, Croatia, Romania and Serbia. They concluded that the Riskmetrics method underestimated VaR in most cases while the GARCH models performed better with Student's t distribution rather than with the normal distribution. Cerovic et al (2015) studied the Montenegrin stock market to compare the GARCH models, EVT and quantile estimation and found that the EVT model performed better than the other models. Gencer and Demiralay (2016) compared the APARCH, FIGARCH and FIAPARCH models using the Student's t distribution and its skewed form to compute VaR values of five emerging economies and resolved that the FIAPARCH model with skewed Student's t distribution gave the best results. They also concluded that the prediction accuracy of the models decrease with increase in the forecasting time horizon. Smolovic et al (2017) evaluated the performance of eight GARCH models (joint ARMA(1,2) with APARCH, T GARCH, GARCH, TS-GARCH, EGARCH , GJR-GARCH and IGARCH) for VaR estimation of stock exchange of Montenegro and found that none of the models considered were capable of accurate VaR estimation.

Thus, there is limited literature on estimation of VaR of emerging economies. As far as India is concerned, there are very limited studies on assessment of VaR. Moreover, there is no significant study on VaR assessment of the Indian gold market. Thus, the study assumes significance taking into consideration the immense love of the Indians to invest in gold.

3. Data and Methodology:

With an objective to develop an intelligent Value at Risk forecasting system for Indian gold prices, the dataset considered for this study comprised of Indian gold prices from January 1, 2009 to March 31, 2017. The total data set comprised of 1985 observations. The data for the Indian gold prices was collected from the website of Multi Commodity Exchange, India Ltd (MCX) which deals with trading in bullion along with the other commodities. The most influential factors that affect the daily gold prices were identified. The factors identified were international oil and gold prices; the US Federal bank interest rate and the US dollar-Rupee exchange rate; the Indian inflation rate, interest rate, BSE stock closing prices, GDP growth rate, gold demand, besides the previous day gold prices (Indian) and the corresponding date. These factors were used for forecasting the one-day ahead gold prices using a hybrid model of IWO and FFBP ANN model. The performance measure values of Coefficient of Correlation (0.99940) and Mean Square Error (0.00001) reported by the model proved the efficacy of the hybrid model for forecasting the Indian prices of gold. The other details of the model are being skipped here for paucity of space. The hybrid model forecasted gold prices were used to forecast the Value at Risk values of trading in the Indian gold market by combining the IWO-FFBP ANN model with the conventional VaR methods, namely, Variance–Covariance (VCV), Historical Simulation (HS) and Monte Carlo Simulation (MC) models. The one day ahead VaR values were computed using these combination models at 95% and 99% confidence levels.

Forecasted return series data was computed from the one day ahead gold prices forecasted by the above mentioned hybrid model. This return series was then used in all the further computations for Value at Risk. Table1 describes the descriptive statistics of the forecasted gold return series.

Table1: Descriptive Statistics of forecasted gold return time series

Statistic	Value	Percentile	Value
Sample Size	1984	Min	-5.936
Range	10.474	5%	-1.2508
Mean	0.03885	10%	-0.8482
Variance	0.71229	25% (Q1)	-0.407
Std. Deviation	0.84397	50% (Median)	0.025
Coef. of Variation	21.723	75% (Q3)	0.464
Std. Error	0.01895	90%	0.9926
Skewness	-0.2146	95%	1.4314
Excess Kurtosis	4.555	Max	4.538

In order to discover the most appropriate distribution which fits the return data series, it was checked against a wide range of data distributions. Further, the Goodness of Fit tests, namely, Kolmogorov Smirnov, Anderson Darling and Chi-Squared Tests were applied. These tests check whether a sample belongs to a population of a particular probability distribution (Chakravart and Roy, 1967), (Stephens, 1974), (Snedecor et al, 1989). The statistic values reported by these tests for the distributions considered for testing goodness of fit alongwith the ranking of the distributions obtained thereof are given in Table 2.Top rank is assigned tothe Burr-Four Parametric distribution by the Kolmogorov Smirnov and Chi-Squared test. Thus, the Burr-Four Parametric distribution is assumed to be the most suitable distribution for the considered time series.

Table 2: Statistical Results of Goodness of fit tests

S.No	Distribution	Kolmogorov Smirnov		Anderson Darling		Chi-Squared	
		Statistic	Rank	Statistic	Rank	Statistic	Rank
1	Burr (4P)	0.02494	1	2.5417	5	18.846	1
2	Error	0.02686	2	1.614	1	27.264	6
3	Laplace	0.02686	3	1.614	2	27.264	7
4	Log-Logistic (3P)	0.02703	4	2.7583	6	22.357	4
5	Johnson SU	0.0274	5	1.8261	3	19.015	2
6	Dagum (4P)	0.02839	6	2.8362	7	25.781	5
7	Hypersecant	0.02843	7	2.3284	4	20.013	3
8	Logistic	0.04029	8	6.4163	8	53.288	8
9	Gen. Extreme Value	0.04984	9	64.902	23	N/A	
10	Cauchy	0.05311	10	15.562	9	158.34	20
11	Pearson 6 (4P)	0.06055	11	17.445	13	130.49	11
12	Beta	0.06083	12	17.42	12	131.49	12
13	Normal	0.06115	13	17.411	11	129.79	10
14	Fatigue Life (3P)	0.06119	14	17.071	10	127.43	9
15	Inv. Gaussian (3P)	0.06315	15	18.381	14	134.32	13
16	Gen. Gamma (4P)	0.06403	16	18.57	16	137.55	16
17	Pearson 5 (3P)	0.06424	17	20.119	18	136.32	15

18	Lognormal (3P)	0.06529	18	18.479	15	139.89	17
19	Erlang (3P)	0.0657	19	21.167	20	146.71	18
20	Gamma (3P)	0.06866	20	20.785	19	155.87	19
21	Error Function	0.0741	21	19.454	17	134.34	14
22	Gumbel Max	0.09537	22	52.478	22	N/A	
23	Gen. Pareto	0.0963	23	430.56	30	N/A	
24	Gumbel Min	0.10179	24	64.918	24	201.03	21
25	Weibull (3P)	0.10465	25	48.33	21	328.14	22
26	Uniform	0.11764	26	371.5	29	N/A	
27	Frechet (3P)	0.13642	27	103.17	26	N/A	
28	Kumaraswamy	0.142	28	93.707	25	638.57	23
29	Pert	0.25135	29	288.98	27	2467.9	25
30	Triangular	0.3091	30	322.55	28	2430.4	24
31	Chi-Squared (2P)	0.37626	31	469.68	31	4869.2	28
32	Rayleigh (2P)	0.41394	32	512.5	32	4300.4	26
33	Power Function	0.4188	33	539.55	33	4728.6	27
34	Exponential (2P)	0.49615	34	691.53	34	10008	29
35	Levy (2P)	0.58604	35	866.18	35	15578	30

Burr, Chi-Squared, Exponential, Inv. Gaussian, Levy, Lognormal, Pareto, Pareto 2, Pearson 5, Pearson 6, Rayleigh, Student's t distributions were also tested. These distributions however were not found suitable for the return series under consideration.

Table 3: Distribution Parameter Estimates of Burr-Four Parametric distribution for forecasted gold return series

	k	α	β	γ
Burr (4P)	0.89947	2.96E+05	1.2481E+05	-1.2481E+05

Hence, Burr-Four Parametric Distribution Function was selected for modeling one day ahead VaR values using the selected conventional VaR methods: VCV, HS and MC at 95% and 99% confidence levels. The VaR values so computed by the three combination models –IWO+FFBPANN and VCV, IWO+FFBPANN and HS, IWO+FFBPANN and MC are thereafter validated by using three back testing techniques, namely, Kupiec test, Christoffersen test and the Joint test to find the most suitable model for forecasting the Value at Risk of Indian Gold market.

4. Results:

The VaR values are computed using the three combination models- IWO+FFBPANN and VCV, IWO+FFBPANN and HS, IWO+FFBPANN and MC. Figs 1 and 2 show the plots of VAR values computed by these models along with the return series plot.

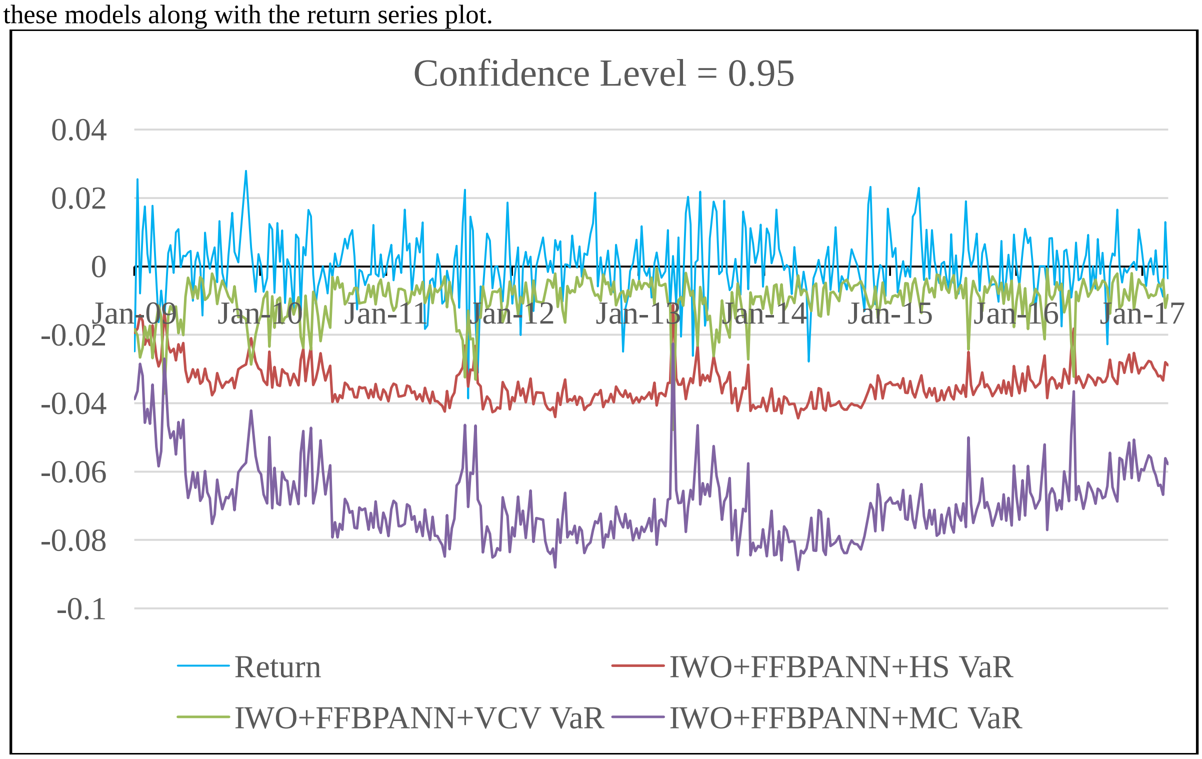

Figure 1: Comparison of Gold Returns with VaR at 95% confidence level for different combination models

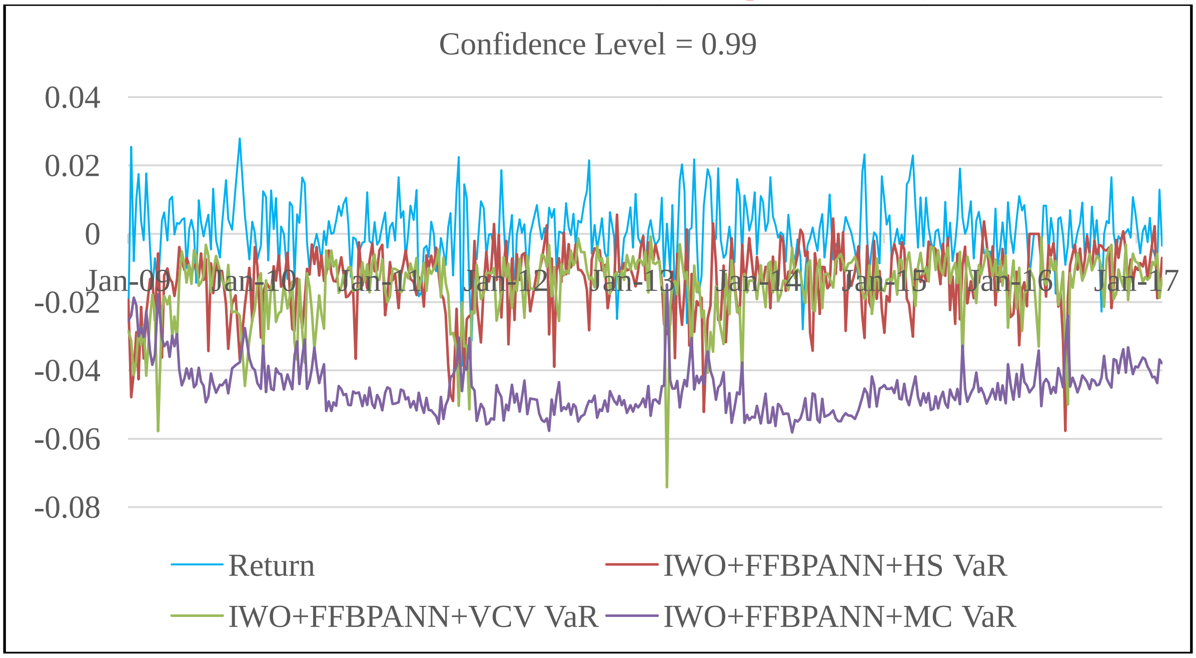

Figure 2: Comparison of Gold Returns with VaR at 99% confidence level for different combination models

The dataset of return series under study is divided into six sets to enable application of the back testing methods. The Kupiec (POF) back testing test is first employed to test statistically the three combination models under study for accurate estimation of proportion of violations or exceptions. Table 4 depicts the results of the Kupiec test for the three combination models for VaR calculations. The Kupiec test results reveal rejection of combination model of MC with hybrid of IWO and FFBPANN for all data sets at both 95% and 99% confidence levels. The IWO+FFBPANN+VCV model is rejected for two data sets at 95% while it fails the test in three data sets at 99% confidence level. The best results are reported by the IWO+FFBPANN+HS model which is accepted for all data sets at 95% confidence level. At 99% it reports acceptance in five out of the six data sets. The IWO+FFBPANN+MC model is rejected by the test as it tend to over-estimate the risk while the IWO+FFBPANN+VCV model faces rejection on count of underestimation of the risk values.

Table 4: Kupiec POF Back Testing Test Results for the Combination Models at 95% and 99%

S.No	Model	Confidence level	No. of observations	Realized number of exceptions	Test statistic LR_{POF}	Critical value χ^2 (1:0.95) and (1:0.99)	Test Result
1	IWO + FFBPANN + VCV Model	95%	350	9	5.25	3.84	Rejected
			350	9	5.25	3.84	Rejected
			350	14	0.79	3.84	Accepted
			350	18	0.01	3.84	Accepted
			350	13	1.33	3.84	Accepted
			228	8	1.19	3.84	Accepted
2	IWO + FFBPANN+ HS Model		350	18	0.01	3.84	Accepted
			350	11	2.91	3.84	Accepted
			350	19	0.13	3.84	Accepted
			350	25	3.00	3.84	Accepted
			350	18	0.01	3.84	Accepted
			228	14	0.58	3.84	Accepted
3	IWO + FFBPANN + MC Model		350	1	28.08	3.84	Rejected
			350	0	-	3.84	Rejected
			350	1	28.08	3.84	Rejected
			350	0	-	3.84	Rejected
			350	0	-	3.84	Rejected
			228	0	-	3.84	Rejected
4	IWO + FFBPANN + VCV Model	99%	350	4	15.73	6.635	Rejected
			350	6	10.55	6.635	Rejected
			350	10	3.98	6.635	Accepted
			350	10	3.98	6.635	Accepted
			350	7	8.50	6.635	Rejected

			228	7	2.06	6.635	Accepted
5	IWO + FFBPANN+ HS Model		350	11	2.91	6.635	Accepted
			350	9	5.25	6.635	Accepted
			350	14	0.79	6.635	Accepted
			350	19	0.13	6.635	Accepted
			350	12	2.04	6.635	Accepted
			228	11	0.01	6.635	Accepted
6	IWO + FFBPANN + MC Model		350	0	-	6.635	Rejected
			350	0	-	6.635	Rejected
			350	1	28.08	6.635	Rejected
			350	0	-	6.635	Rejected
			350	0	-	6.635	Rejected
			228	0	-	6.635	Rejected

In the second stage of validation of the considered VaR combination models, Christoffersen Independence Test was applied. Table 5 illustrates the input data computed for the LR_{ind} statistic of the Christoffersen test. This test which checks for serial independence of the exceptions or absence of exception clustering, reports acceptance for IWO+FFBPANN+VCV and IWO+FFBPANN+HS at 95% for all the data sets. These models report good performance at 99% also while exhibiting similar results of acceptance for five data sets. However, the IWO+FFBPANN+MC is rejected for all the six data sets, both at 95% as well as at 99% confidence levels as it inclines to overestimate the risk values.

Table 5: Independence Test Input data

S.No	Model	Confidence level	No. of observations	Realized number of exceptions	Independence Test Data						
					T_{00}	T_{01}	T_{10}	T_{11}	π_0	π_1	π
1	IWO + FFBPANN + VCV Model	95%	350	9	53	7	8	1	0.13	0.13	0.13
			350	9	54	7	7	1	0.11	0.13	0.12
			350	14	42	12	12	3	0.22	0.20	0.22
			350	18	43	10	9	7	0.17	0.41	0.23
			350	13	45	10	10	4	0.18	0.29	0.20
			228	8	35	6	7	2	0.17	0.25	0.18
2	IWO + FFBPANN + HS Model		350	18	38	14	15	2	0.28	0.13	0.25
			350	11	51	8	8	2	0.14	0.20	0.14
			350	19	34	14	14	7	0.29	0.33	0.30
			350	25	34	13	12	10	0.26	0.43	0.32
			350	18	37	12	12	8	0.24	0.40	0.29
			228	14	27	8	9	6	0.25	0.43	0.30
3	IWO + FFBPANN + MC Model		350	1	67	1	1	0	0.01	0.00	0.01
			350	0	69	0	0	0	0.00	-	0.00
			350	1	67	1	1	0	0.01	0.00	0.01
			350	0	69	0	0	0	0.00	-	0.00
			350	0	69	0	0	0	0.00	-	0.00
			228	0	50	0	0	0	0.00	-	0.00
4	IWO + FFBPANN + VCV Model	99%	350	4	63	2	3	1	0.05	0.33	0.06
			350	6	60	4	4	1	0.06	0.20	0.07
			350	10	48	10	10	1	0.17	0.09	0.16
			350	10	53	8	7	1	0.12	0.11	0.12
			350	7	53	8	8	0	0.13	0.00	0.12
			228	7	37	5	6	2	0.14	0.29	0.16
5	IWO + FFBPANN + HS Model		350	11	49	9	10	1	0.17	0.10	0.16
			350	9	55	7	7	0	0.11	0.00	0.10
			350	14	41	12	12	4	0.23	0.25	0.23
			350	19	39	13	12	5	0.24	0.28	0.25
			350	12	46	9	10	4	0.18	0.31	0.20
			228	11	31	8	8	3	0.21	0.27	0.22
6	IWO + FFBPANN + MC Model		350	0	69	0	0	0	0.00	-	0.00
			350	0	69	0	0	0	0.00	-	0.00
			350	1	67	1	1	0	0.01	0.00	0.01
			350	0	69	0	0	0	0.00	-	0.00
			350	0	69	0	0	0	0.00	-	0.00
			228	0	50	0	0	0	0.00	-	0.00

Table 6: Christoffersen Independence Test Results for the combination models at 95% and 99% confidence levels

S.No	Model	Confidence level	No. of observations	Realized number of exceptions	Test statistic LR_{IND}	Critical value χ^2 (1:0.95) and (1:0.99)	Test Result
1	IWO + FFBPANN +	95%	350	9	0.00	3.84	Accepted
			350	9	0.01	3.84	Accepted

	VCV Model		350	14	0.03	3.84	Accepted
			350	18	3.78	3.84	Accepted
			350	13	0.70	3.84	Accepted
			228	8	0.29	3.84	Accepted
2	IWO + FFBPANN + HS Model		350	18	1.84	3.84	Accepted
			350	11	0.27	3.84	Accepted
			350	19	0.12	3.84	Accepted
			350	25	2.09	3.84	Accepted
			350	18	1.61	3.84	Accepted
			228	14	1.48	3.84	Accepted
3	IWO + FFBPANN+ MC Model		350	1	-	3.84	Rejected
			350	0	-	3.84	Rejected
			350	1	-	3.84	Rejected
			350	0	-	3.84	Rejected
			350	0	-	3.84	Rejected
			228	0	-	3.84	Rejected
4	IWO + FFBPANN+ VCV Model	99%	350	4	2.32	6.635	Accepted
			350	6	0.95	6.635	Accepted
			350	10	0.52	6.635	Accepted
			350	10	0.00	6.635	Accepted
			350	7	-	6.635	Rejected
			228	7	0.84	6.635	Accepted
5	IWO + FFBPANN + HS Model		350	11	0.34	6.635	Accepted
			350	9	-	6.635	Rejected
			350	14	0.04	6.635	Accepted
			350	19	0.13	6.635	Accepted
			350	12	1.01	6.635	Accepted
			228	11	0.22	6.635	Accepted
6	IWO + FFBPANN + MC Model		350	0	-	6.635	Rejected
			350	0	-	6.635	Rejected
			350	1	-	6.635	Rejected
			350	0	-	6.635	Rejected
			350	0	-	6.635	Rejected
			228	0	-	6.635	Rejected

Finally, at the third stage of validation of the considered models, Joint Test which checks for both the independence of exceptions as well as unconditional coverage, is applied. This test examines jointly both these properties together and helps detect the VaRs that lack in either of these two properties (Campbell, 2005). The Joint Test results for the combination models are displayed in Table 7. The IWO+FFBPANN+MC combination model is rejected by this test for all the data sets, both at 95% as well as 99% confidence level. This model again tends to overestimate the risk values and thus faces rejection. The IWO+FFBPANN+VCV exhibits good performance at 95% as it is accepted in all the cases, but at 99% confidence level, the Joint Test reports its rejection in three of the six data sets on account of under estimation of risk values for these data sets. The best results are reported by the IWO+FFBPANN+HS combination model. The test reports its acceptance for all the six data sets at both 95% and 99% confidence levels.

Table 7: Joint Test results for the combination models at 95% and 99% confidence levels

S.No	Model	Confidence level	No. of observations	Realized number of exceptions	Test statistic LR_{joint}	Critical value χ^2 (2:0.95) and (2:0.99)	Test Result
1	IWO + FFBPANN + VCV Model	95%	350	9	5.25	5.99	Accepted
			350	9	5.25	5.99	Accepted
			350	14	0.82	5.99	Accepted
			350	18	3.80	5.99	Accepted
			350	13	2.03	5.99	Accepted
			228	8	1.48	5.99	Accepted
2	IWO + FFBPANN + HS Model		350	18	1.85	5.99	Accepted
			350	11	3.18	5.99	Accepted
			350	19	0.25	5.99	Accepted
			350	25	5.09	5.99	Accepted
			350	18	1.62	5.99	Accepted
			228	14	2.06	5.99	Accepted
3	IWO + FFBPANN + MC Model		350	1	28.10	5.99	Rejected
			350	0	-	5.99	Rejected
			350	1	28.10	5.99	Rejected
			350	0	-	5.99	Rejected
			350	0	-	5.99	Rejected
			228	0	-	5.99	Rejected
4	IWO + FFBPANN + VCV Model	99%	350	4	18.05	9.21	Rejected
			350	6	11.49	9.21	Rejected
			350	10	4.49	9.21	Accepted

			350	10	3.98	9.21	Accepted
			350	7	-	9.21	Rejected
			228	7	2.90	9.21	Accepted
5	IWO + FFBPANN + HS Model		350	11	3.25	9.21	Accepted
			350	9	-	9.21	Rejected
			350	14	0.83	9.21	Accepted
			350	19	0.26	9.21	Accepted
			350	12	3.04	9.21	Accepted
			228	11	0.24	9.21	Accepted
6	IWO + FFBPANN+ MC Model		350	0	-	9.21	Rejected
			350	0	-	9.21	Rejected
			350	1	-	9.21	Rejected
			350	0	-	9.21	Rejected
			350	0	-	9.21	Rejected
			228	0	-	9.21	Rejected

5. Conclusion:

This paper proposes an intelligent Value at Risk Model combination model of Historical Simulation with hybrid of Invasive Weed Optimization (IWO) Model and Feed Forward Back Propagation Artificial Neural Network (FFBPANN). This model forecasts one day ahead Value at Risk values for the Indian gold market. One day ahead gold prices are initially forecasted with the help of a hybrid of IWO and FFBPANN model. The one day ahead return values are computed from the forecasted prices. In order to find the best distribution that fits the return series, it is tested for a wide range of distributions. Goodness of fit tests, namely, Kolmogorov Smirnov, Anderson Darling and Chi-Squared tests are applied to find the best distribution that fits the data series. As per the results obtained, Burr-Four Parametric distribution is chosen as the best fitting distribution. The hybrid model of IWO and FFBPANN model from which the return values are obtained, is then combined with the three conventional models, namely, Variance-Covariance, Historical Simulation and Monte Carlo Simulation methods for calculation of VaR values. These three combination models are then validated by applying the Back Testing methods, namely, the Kupiec test, Christoffersen's test and the Joint test to find the best VaR forecasting model. The combination model of Historical Simulation (HS) and IWO-FFBPANN model is reported as the best model by these tests. A unique intelligent combination model HS+ IWO+FFBPANN model, capable of forecasting efficiently the VaR values for the Indian gold market is proposed as a result of the study.

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