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Performance Analysis of Best Replacement Optimization Model in Stock Market Forecasting

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Abstract— Stock Price Prediction is one of the emerging fields of research and many method's like technical analysis, statistical methods, time series analysis etc are used for this purpose. In this paper, we have presented a Best Replacement Optimization (BRO) approach to predict stock market data. S&P CNX Nifty Fifty indices are used as sample data set to validate the concept. The performance of this model is analysed by comparing with Hidden Markov Model and Particle Swarm Optimization Techniques.

Index Terms—Stock Market, Particle swarm optimization, Best Replacement Optimization.

1. INTRODUCTION

The present financial world stock market forecasting is considered as one of the most challenging tasks. So, lot of attention has been given to analyze and forecast future vale and behavior of financial time series. Different factors interact in stock market such as business cycles, interest rates, monitory policies, general economic conditions, traders' expectations, political events, etc., According to academic investigations, movements in market prices are random rather they behave in a highly non-liner, dynamic manner [2]. Ability to predict direction and correct value of future stock market value is the most important factor in financial market to make money. These days because of online trading, stock market has become one of the hot targets where anyone can earn profits. So, forecasting the correct value and behavior of stock market has become the area of interest.

A lot of researches were conducted and many forecasting model have been proposed. Hidden Markov Model was first described by Leonard E. Baum in 1960s and has been used in analyzing and predicting time series phenomena such as speech recognition [6], ECG[3] analysis and DNA sequencing [1]. In [6], the authors explained basis of HMM and how it can be used in signal prediction. The stock prediction problem is similar to these problems in its inherent time-dependence; however the application of HMMs to stock market is still relatively limited. In [5], the authors used HMM for forecasting stock markets.

Particle swarm optimization (PSO) is a population based stochastic optimization technique developed by Dr. Eberhart and Dr. Kennedy in 1995, inspired by social behavior of bird flocking or fish schooling. In [4], the authors presented the comparison of two meta-heuristic approaches: Differential Evaluation and Partial Swam Optimization in the training of feed forward network to predict the daily stock prices. In [7], the authors introduced the PSO technique to develop an efficient forecasting model for prediction of various stock indices.

In this paper, BRO Algorithm as a modified version of PSO Algorithm is used to predict the stock market and then compare this model with HMM and PSO model.

2. METHODOLOGY

Secondary data was obtained from yahoo finance. BRO Algorithm methods are used for predicting stock prices. The performance of this model is then analyzed by comparing with Hidden Markov Model and PSO Algorithm. Forecasting efficiency was derived based on following error measures MAE – Mean Absolute Error, RMSE – Root Mean Square Error and MSE – Mean Square Error.

Particle swarm optimization

PSO simulates the behaviors of bird flocking. Suppose the following scenario: a group of birds are randomly searching food in an area. There is only one piece of food in the area being searched. All the birds do not know where the food is. So what's the best strategy to find the food? The effective one is to follow the bird which is nearest to the food. PSO learned from the scenario and used it to solve the optimization problems. In PSO, each single solution is a "bird" in the search space. We call it "particle". All of particles have fitness values which are evaluated by the fitness function to be optimized, and have velocities which direct the flying of the particles. The particles fly through the problem space by following the current optimum particles.

PSO is initialized with a group of random particles (solutions) and then searches for optima by updating generations. In every iteration, each particle is updated by following two "*best*" values. The first one is the best

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solution (fitness) it has achieved so far. (The fitness value is also stored.) This value is called $pbest$. Another "$best$" value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the population. This best value is a global best and called $gbest$. When a particle takes part of the population as its topological neighbors, the best value is a local best and is called $lbest$.

After finding the two best values, the particle updates its velocity and positions with following equation (1) and (1).

$$v[\ ] = v[\ ] + c_1 * \text{rand}(\ ) * (\text{pbest}[\ ] - \text{present}[\ ]) + c_2 * \text{rand}(\ ) * (\text{gbest}[\ ] - \text{present}[\ ]) \quad (1)$$

$$present\ [\ ] = present\ [\ ] + v\ [\ ] \quad (2)$$

$v[\ ]$ is the particle velocity, $present[\ ]$ is the current particle (solution). $pbest[\ ]$ and $gbest[\ ]$ are defined as stated before. $rand\ (\ )$ is a random number between (0,1). c_1, c_2 are learning factors (weight).

Inertia Weight

D is the dimension, c_1 and c_2 are positive constants, $rand_1$ and $rand_2$ are random numbers, and w is the inertia weight

$$v_{id}^{new} = w_1.v_{id}^{old} + c_1.rand_1.(p_{id} - x_{id}) + c_2.rand_2.(p_{gd} - x_{id}) \quad (3)$$

$$x_{id}^{new} = x_{id}^{old} + v_{id}^{new} \quad (4)$$

Velocity can be limited to v_{max}.

This equation (3) taken in account from the PSO algorithm and it is modified as BRO Algorithm based on processing value of iteration. The BRO Algorithm set the treat hold value of global value as the limitation of iteration.

$$lim \rightarrow limit\ of\ iteration$$
$$lim_{max} \rightarrow threshold\ of\ Global\ fitness\ value$$
$$(or)$$
$$\pm i\ of\ Global\ fitness\ value\ where\ i < Max\ GFV$$

$$v_{id}^{new} = \sum_{i=0}^{lim_{mam}} \left(w_1.v_{id}^{old} + c_1.rand_1.(p_{id} - x_{id}) + c_2.rand_2.(p_{gd} - x_{id}) \right) \quad (4)$$

where c_1 is average of before 2 years value from the particle and c_2 is average of after 2 years value from the particle

Procedure for BRO Algorithm

Step1: Initialize position and velocity of all the particles randomly in the N dimension space.
Step2: Evaluate the fitness value of each particle, and update the global optimum position.
Step3: According to changing of the gathering degree and the steady degree of particle swarm, determine whether all the particles are re-initialized or not.
Step4: Determine the individual best fitness value. Compare the l_p of every individual with its current fitness value. If the current fitness value is better, assign the current fitness value to l_p.
Step5: Determine the current best fitness value in the entire population. If the current best fitness value is better than the g_p, assign the current best fitness value to g_p.
Step6: For each particle, update particle velocity,
Step7: Repeat the iteration of the particle using $gbest$ fitness value and limit the Iteration of the particle.
Step8: Update particle position.
Step9: Repeat Step2 - 7 until a stop criterion is satisfied or a predefined number of iterations are completed. While maximum iterations or minimum error criteria is not attained Particles' velocities on each dimension are clamped to a maximum velocity v_{max}. If the sum of accelerations would cause the velocity on that dimension to exceed v_{max}, which is a parameter specified by the user. Then the velocity on that dimension is limited to v_{max}.

Weight Updation using BRO:

The optimal BRO parameters have been determined by varying the inertia weight (w_i), maximum velocity (v_{max}), social and cognitive coefficient (c_1 and c_2) and the particle size and the values of the parameters for which we have found the best result in our data set are as follows:

Inertia weight= 102025257
Maximum velocity= 686898999
Particle size = 4000

3. COMPARISON OF MODELS

In this section, the forecasted values obtained from the BRO model is compared with HMM and PSO model. S&P CNX Nifty 50 index values are used to test the efficiency of proposed BRO method.

3.1. Data Set Used:

Historical Stock Price data (from 01.01.1997to30.04.2013) of S&P CNX Nifty 50 collected from http://in.finance.yahoo.com

3.2. Result

Data from 01.01.1997 to 30.04.2013 (total 4076 data) is used to predict the stock share traded value. The table 1 given below is showing the predicted value and percentage relative error in prediction for random days.

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Table 1: Predicting price, Actual price and Error (%) of share traded value

Date	Actual	Predicted Value			Error(%)of share traded value		
		HMM	PRO	BRO	HMM	PRO	BRO
2/19/2007	59419122	59360471.48	59392508.4	59399122.19	0.098706	0.04479	0.033659
9/1/2009	332639046	332574110.5	332613683	332619046.3	0.019521	0.007625	0.006012
6/27/2011	143402407	143331142.4	143378602	143382407.5	0.049696	0.0166	0.013946
8/3/2012	112918653	112849945.4	112893092	112898653.3	0.060847	0.022637	0.017712
2/1/1999	23175431	23092873.38	23154417.4	23155431.48	0.356229	0.090672	0.086296
7/25/2003	85402139	85328125.27	85374187.5	85382139.39	0.086665	0.032729	0.023418
5/19/2005	42626009	42566810.17	42596843.3	42606009.48	0.13888	0.068422	0.046919
3/14/2007	83325778	83247001.29	83302140.5	83305778.19	0.094541	0.028368	0.024002
10/15/2007	160987288	160907215.2	160965409	160967288.5	0.049739	0.013591	0.012423
1/6/2009	340452916	340358811.3	340423737	340432916.2	0.027641	0.008571	0.005874
11/1/2010	128909525	128859446.4	128885563	128889525.4	0.038848	0.018588	0.015514
12/2/1997	43427325	43376257.39	43405325.5	43407325.28	0.117593	0.050658	0.046053
9/27/1999	46403334	46316447.17	46381794.5	46383334.28	0.187243	0.046418	0.0431
3/11/2005	70474058	70405377.29	70450652.5	70454058.17	0.097455	0.033212	0.028379
1/4/2007	67096186	67034482.18	67074949.5	67076186.37	0.091963	0.031651	0.029807
10/20/1999	56371669	56315029.17	56343114.5	56351669.48	0.100476	0.050654	0.035478
8/14/2001	42862979	42800653.28	42834532.5	42842979.18	0.145407	0.066366	0.04666
6/9/2003	58750135	58692341.28	58723824.5	58730135.27	0.098372	0.044784	0.034042

Figure1: Forecasting Methods

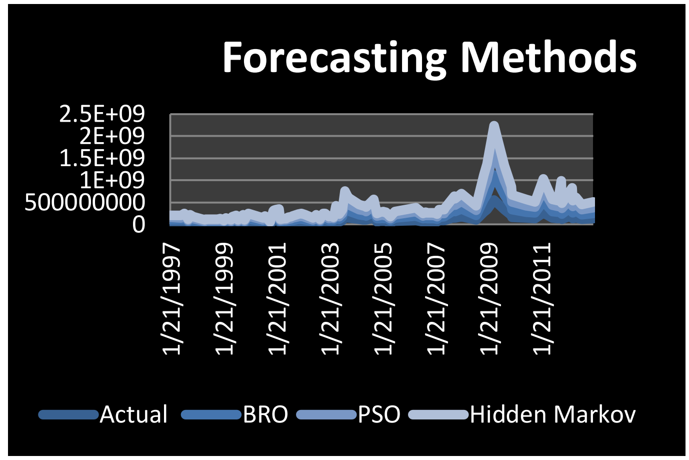
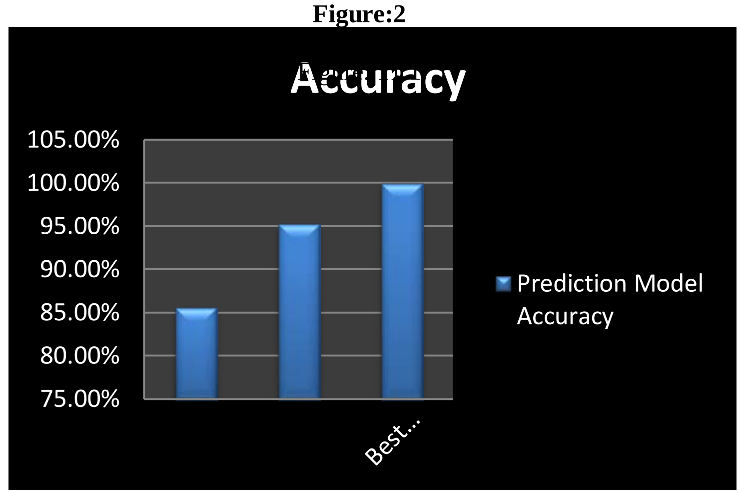


Table 2: Error performance measurements

Prediction Model	Test Type			Accuracy
	MAE	RMSE	MSE	
Hidden Markov Model	0.144132	74947.59	5617141565	85.59%
Particle Swam Optimization	0.0475278	24946.92761	622349197	95.25%
Best Replacement Optimization	0.000344	19899.42112	395986961	99.96%

Figure:2



4. CONCLUSION

In this paper, we have analysed the performance of BRO forecasting model. This paper not only comes out with a model of forecasting but also compares the result

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with existing HMM and PSO model and provides enough evidence why this method performs better than those models.

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