International Journal of Applied Engineering Research ISSN 0973-4562 Volume 12, Number 23 (2017) pp. 13399-13404
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A Comparative Study on Cash Management Models using Soft Computing Techniques

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Abstract

Cash is the need in finance used by banks and industries to satisfy the customer on daily basis. Difficulty in cash management decision making is that to attain a higher customer satisfaction bank needs to maintain a large amount of money would incur a high expenditure. In this paper linear PSO (Particle swarm optimization) and GSA (Gravitational Search Algorithm) models are proposed for estimating daily cash requirement of a bank by considering the variables, Day Of the Month (DOM), Day Of the Week (DOW), Salary day Effect (SE), Holiday Effect (HE) . The algorithms for estimating both the model coefficients for short term is implemented from the actual data of a particular bank branch, using PSO and GSA in MATLAB. A fitness function is used to minimize the total cost of the proposed system. The models are then used for future cash management for validation and it was found that the results are in good agreement with the observed data and PSO based cash management model outperformed other model with better accuracy.

Keywords: Cash forecasting, optimization, Minimization, PSO,GSA, Daily Model.

INTRODUCTION

Optimized cash management is the need in finance used by banks and industries to produce optimal strategies that are able to minimize the daily amount of the required money, still assuring for the effective customer service. Difficulty in cash management decision making is that to attain a higher customer satisfaction bank needs to maintain a large amount of money would incur a high expenditure. Linear regression techniques were used by the researchers as forecasting tool. It is a simple mathematical model easy to implement and understand.

It is an estimation technique that uses statistical relationship between historical data and other variables. The objective of the moving average models is to discover the pattern in the historical data series. The model coefficients are statistically estimated and used for future anticipation of cash. The inherent problems with the moving average is the inaccuracy of prediction and numerical instability when there is an abrupt change in the environment or sociological variables that affects the cash pattern like salary days, holidays.

The financial forecasting system modeling is aimed at minimizing the error between the actual value and the model's output value. The commonly adopted strategy for financial modeling using actual data are least square and maximum likelihood (ML) methods implemented recursively using measured input and output data (Yin. L,et.al,2001) . They are essentially local search techniques, search for the optimum by gradient methods and often fail in the search global minima. Therefore an effective method for parameter estimation of financial forecasting models should be investigated.

The EP is most suitable for dynamic environment. It mimics the human decision making process by planning, recognizing the surroundings, predicting the future expected output. It is also used to solve non-linear and quadratic optimization problems (Myung H and Kim JH, 1996).The use of EA in prediction approach used the different learning methods to find the best optima in the given problem space (Eggermont et al., 2001). It was also used by the researchers in forecasting techniques to estimate the best values in a dynamically changing environment. The two different models were developed for prediction using linear regression (Simoes and Costa, 2008) and nonlinear regression to determine the best value in the fast changing environment (Simoes and Costa,2009).

PARTICLE SWARM OPTIMIZATION.

A new stochastic based optimization algorithm "Particle Swarm Optimization" (PSO), was introduced to solve non-linear problems (R.C.Eberhart and Kennedy,1995). PSO simulates the social behavior of swarms and their mathematical models used in the algorithm to efficiently generate a global optimum solution to a large number of problems in various fields of science, engineering and continuous function optimization (R.C.Eberhart and Kennedy,1995) .

The researchers tried for better optimization in different fields using proper parameter selection such as flow shop scheduling (Ching-Jong Liaoa et al., 2007) job shop scheduling (Z.Lianao et al., 2006), the engineering optimization (Z.Lian et al.,2006 and X.Hu et al, 2001) and others (J.Kennedy and Eberhert,2001 and Y.H.Shi and Eberhert,2001). PSO was introduced to identify the best global convergence in a dynamically changing environment (Ratnaweera et al., 2004).In multi-dimensional space variation space along with the particle velocity improves the convergence speed (Chattarjee and Siarry,2006).To update the velocity and the position in the PSO equation Gaussian mutation has been introduced (Higashi & Iba, 2001).The above literature study helps to understand and design cash management model using the constructive and cooperative learning strategy.

The objective function is optimized using PSO by making a populace of potential arbitrary results known as particles. They are assigned with randomized velocity and moves through problem space. The particle remembers its historical best value known as local best, Pbest, and share the data with other particles to find the global best, gbest, among all, based on fitness function enhancement.

The updating of the velocity and location of particle continues based on the Pbest, and best of all the particles until the maximum number of particle converges to optimal value. Let the number of particles used in the problem domain is swarm size, m. The position of the particle, i, in the multidimensional space is considered as position vector $X_i=[x_{i1}, x_{i2},\dots, x_{iD}]$ and their corresponding velocity is expressed as velocity vector $V_i=[v_{i1}, v_{i2}, \dots, v_{iD}]$. The best position of the particle i, Pbest, in the previous iteration is denoted as $P_i=[p_{i1}, p_{i2},\dots, p_{iD}]$.

The historical best value of gbest is one among the P_i, which has the highest objective function in previous iteration is Pgd. The velocity and the position of individual swarm particle is updated using the following notations (1.1) and (1.2), respectively:

$$\mathrm{v}_{\mathrm{id}}^{\mathrm{n}+1} = \mathrm{w}\,\mathrm{v}_{\mathrm{id}}^{\mathrm{n}} + \mathrm{c}_1\mathrm{r}_1^{\mathrm{n}}(\mathrm{p}_{\mathrm{id}}^{\mathrm{n}} - \mathrm{x}_{\mathrm{id}}^{\mathrm{n}}) + \mathrm{c}_2\mathrm{r}_2^{\mathrm{n}}\left(\mathrm{p}_{\mathrm{gd}}^{\mathrm{n}} - \mathrm{x}_{\mathrm{id}}^{\mathrm{n}}\right) \qquad (1.1)$$

$$\mathrm{x}_{\mathrm{id}}^{\mathrm{n}+1} = \mathrm{x}_{\mathrm{id}}^{\mathrm{n}} + \mathrm{v}_{\mathrm{id}}^{\mathrm{n}+1} \qquad (1.2)$$

$\mathrm{v}_{\mathrm{id}}^{\mathrm{n}+1}$is the velocity of the particle.

$\mathrm{x}_{\mathrm{id}}^{\mathrm{n}+1}$is the position of the particle

c_1, c_2 are the cognitive and social factors, $c_1 = c_2 = 2$.

*w*is the weight .

r1, r2 are the random numbers within the interval of [0,1]. n is the number of iterations.

GRAVITATIONAL SEARCH ALGORITHM

It is an heuristic based optimization algorithm, which is basically used to solve complex problems using law of gravity and mass (Esmat and etal.,2009). It was inspired by natural phenomena. Law of gravity defines that every agent attracts another agent due to its gravitational force .The agent which has more mass can easily attracts the agent with the lesser mass in the problem space to find the optimal solution (Taisir and Qasim, 2013). The agents in the problem space is defined using the following equation (1.3).

$$\mathrm{x_i} = \left(\mathrm{x_i^1}, \mathrm{x_i^2}, \mathrm{x_i^3}, \dots, \mathrm{x_i^d}, \dots \mathrm{x_i^n}\right) \qquad (1.3)$$

where n is dimension ,$\mathrm{x_i^d}$ is the position.

The agents were scattered in the problem space randomly, which is defined using the gravitational force is defined in the equation (1.4).

$$\mathrm{F_{ij}} = \mathrm{G(t)} = \frac{\mathrm{Mi(t)*Mj(t)}}{\mathrm{Rij(t)+\epsilon}}\{\mathrm{Xj(t) - Xi(t)}\} \qquad (1.4)$$

Mi and Mj are agents, i and j are its mass, Rij (t) is the distance between the agents, G (t) is gravitation constant with respect to time. The randomly initialized gravitational constant G, decreases by time, t, to control the search's accuracy. Thus G is a function of initial value (G0) and time (t). The total force acting upon the individual agent is defined in the equation (1.5).The acceleration of an agent in the search space at a particular time 't' is directly proportional to its force and inversely proportional to its mass is defined in the equation (1.6).

$$\mathrm{Fid} = \textstyle\sum_{\mathrm{rand(i)*Fij}} \mathrm{rand(i) * Fij} \qquad (1.5)$$

$$\mathrm{Aid(t)} = \frac{\mathrm{Fid(t)}}{\mathrm{Mij(t)}} \qquad (1.6)$$

The speed at which the agents defined in problem space are attracted with each other using the current acceleration were updated using the velocity update equation defined in(1.7) and (1.8).The mass of a particular agent can be calculated using the equation(1.9).

$$vid(t+1) = rand(i) * vid(t) + Aid(t) \qquad (1.7)$$

$$xid(t+1) = xid * vid(t+1) \qquad (1.8)$$

$$\mathrm{Mi(t)} = \frac{\mathrm{Fit(i)-worst(t)}}{\mathrm{best(t)-worst(t)}} \qquad (1.9)$$

Where vidis the velocity, rand is the random value between 0 and 1,xid is the position, Fit(t) is fitness value of an agent i at time t. Best(t) and worst(t) indicates the strongest and weakest agents based on to their fitness value is defined in the equation (1.10) and (1.11).

$$\mathrm{worst(t)} = \max_{\mathrm{j\in\{1,2,\dots,N\}}} \mathrm{Fit(t)} \qquad (1.10)$$

$$\text{best}(t) = \min_{j\in\{1,2,\dots,N\}} \text{Fit}(t) \qquad (1.11)$$

The aforementioned equations were used to identify the optimal values to find out the actual cash requirement of a bank branch using gravitational force technique.

PROPOSED CASH MANAGEMENT MODEL

In this study a linear PSO and GSA models are proposed for estimating daily cash requirement of a bank by considering the variables, Reference Year (RY),Month of the Year (MOY), Day Of the Month (DOM), Day Of the Week (DOW), Salary day Effect (SE), Holiday Effect (HE). The model coefficients for PSO and GSA models were implemented for short term data which is defined in the equation 1.12. The parameter selection for short term cash forecasting in which four input parameters were used for short term forecasting which was less than one year, such as DOM,DOW,SE,HE, since the forecasting has been made for 60 days.

The historical data available from the bank for less than one year is used for short term , the parameters used in the proposed study are. i). DOM(Range:1 to 27), ii). DOW (Range: 1 to 6), iii). HE (Range: 0,1) iv). SE (Range: 0 to1). In DOM the first working day of the month is assigned as the value of 1, which will be incremented by 1, for all working days of a particular month and the maximum number of working days present in our data set is 27. For DOW the Monday of the week is assigned as 1, and incremented by 1 till Saturday which has the maximum value of 6. The day before and after a particular holiday are assigned the value of HE as 1 and for the remaining days as 0. The SE which has the effect on the beginning of the month is assigned the value of 1, 2 and 3 for the first three working days and 0 for the remaining days. The PSO and GSA models are proposed which takes into effect of all the variables for short term data is defined in the equation (1.12).

$$F_t = Ca_0+Ca_1*DOM+Ca_2*DOW+ Ca_3 *HE +Ca_4 * SE \qquad (1.12)$$

where Ca0, Ca1, Ca2, Ca1and Ca4 are the coefficients to be determined using PSO and GSA , Ft is the cash forecast fitness function.

COEFFICIENTS ESTIMATION BY PSO AND GSA

The aim of this proposed study is to optimize the aforementioned coefficients based on the PSO and GSA algorithm from the actual historical cash requirement data. The number of parameters used in both the models shows effect of the above mentioned variables The estimated coefficients of each model after considering the input parameters is clearly shown in the table 1.1. The model parameter can be evaluated to reduce the error between the existing cash requirement and the simulated cash forecast output using the fitness function ,f, for the PSO and GSA is defined in the equation (1.13)

$$f = \min(\textstyle\sum_{i=1}^{n}[Cashforecast - Cashactual]^2) \qquad (1.13)$$

where n represents the experimental data set values.

PERFORMANCE METRICS

The error between the actual and forecast data is estimated using i) Mean Absolute Error (MAE) ii) Mean Absolute Percentage Error (MAPE) iii) Mean Square Error which are defined as follows.

$$\text{MAE} = \frac{\sum(X_t - F_t)}{n} = \frac{\sum e_t}{n} \qquad (1.14)$$

$$\text{MAPE} = \frac{\sum\left|\frac{X_t - F_t}{X_t}\right|}{n}(100) = \frac{\sum\left|\frac{e_t}{X_t}\right|}{n}(100) \qquad (1.15)$$

$$\text{MSE} = \frac{\sum|X_t - F_t|^2}{n} \qquad (1.16)$$

where x_t is the actual data at period t, F_t is the forecast at period, t, e_t is the forecast error at period t, while n is the number of observations.

EXPERIMENTAL RESULTS

The daily cash requirement form the historic data for short term was used to optimize the cash management process. The iterative method of multiple linear regression using PSO and GSA were proposed to find the coefficient for Ca_0, Ca_1, Ca_2, Ca_3, Ca_4 which is the short term data.

The convergence of PSO and is influenced by swarm size, maximum iteration , the inertia weight 'w' which considers both local and global exploration abilities and random numbers to maintain population diversity. The particles in the problem space were assigned with the initial random values ranges between 0 and 1. Each particles has its own initial random position and velocity. Each particles moves from one place to another place based on its velocity and its position. The particles has it own memory to share their knowledge to reach the closest local best and hence reaches the global best. So, that the minimizing function equation (1.13) reaches it global minima.

In the proposed model the different number of trials were made using PSO and then the following parameters values are selected as: i) the linearly varying inertia weight, w, decreases from 0.9 to 0.5, as a function of maximum iteration. If w is assigned to 0.1 the velocity of the particle will change instantly, if the particle moves far away from its best known position of P_{best} and g_{best} which favours the local search, however when w is set to 0.9, the changing velocity is lower , favours exploration ii) c1, c2 are the cognitive and social parameter assigned as c1=2, c2=2 which is used as the parameters for proposed model , proper selection gives better convergence rate iii) the search space dimension, D varies from 1 to 6 based on the number of coefficients in PSO. In the initial stage 10,20 is set as swarm size , different runs were made and the convergence towards single value is achieved faster, however there is chance of local minima. The number of swarms were increased and the number of iterations for various runs in which the fitness function depicted in the proposed model is capable of providing a near optimal solution with a swarm population size as 20 and the maximum number of iterations as 100.

In GSA, each particle has its own position, its inertial mass, active gravitational mass and passive gravitational mass. The GSA parameters used in the cash management model uses the number of mass as 30,initial position and velocity are random values between 0 and 1,gravitional constant(G) is 1.It uses exploration and exploitation which is used to find the optimal values The exploitation feature helps the agents to move towards the agent which has the heavier mass. The values forG and M were calculated to update the position for each iteration until it reaches the optimal solution .The obtained results were tested using evaluation metrics, the run which minimizes the fitness function was selected as the model parameters and the same is available for both PSO and GSA are tabulated in Table 1.1 and Table 1.2.The optimized cash management model coefficients for PSO , the swarm population size of 20 and the number of agents were 30 chosen with maximum iterations of 100 and 200 for both PSO and GSA.

Table 1.1 Parameter estimation for short term data Model using PSO and GSA

Model Number	Ca_0	Ca_1	Ca_2	Ca_1	Ca_4
PSO	5.7167	-0.1961	0.0978	-0.0250	5.1011
GSA	0.2877	0.2378	0.6810	1.1970	5.4350

Using these coefficients in the model equation 1.12, the cash requirement is forecasted for the known 12 data set for short term , results were compared and plotted in Fig.1.1.The performance MAE, MAPE, MSE for the validated data of both the models were tabulated in Table 1.2.

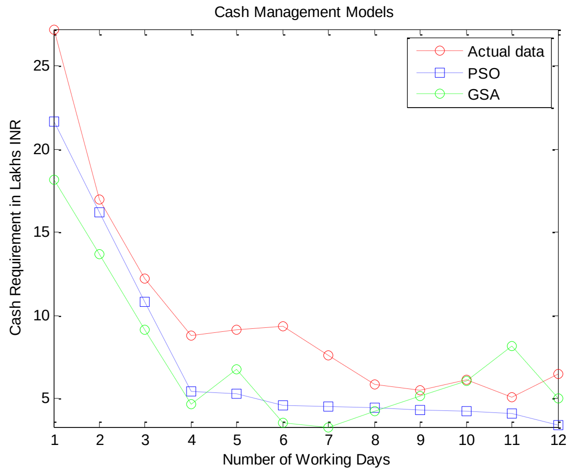

Figure 1.1: Cash Management Models

The statistical anticipation methods like Moving Average Model, Holtz Anticipation Model, exponential smoothing model uses only one variable, i.e., the historic actual cash requirement data (Fraydoon and et.al., 2010).The above graph mentioned in the Fig.1.1 shows the influence of all the input parameters used in the proposed study are compared with the actual data set . The performance of the existing forecasting methods were compared with the actual data and the same is plotted in Fig.1.2.

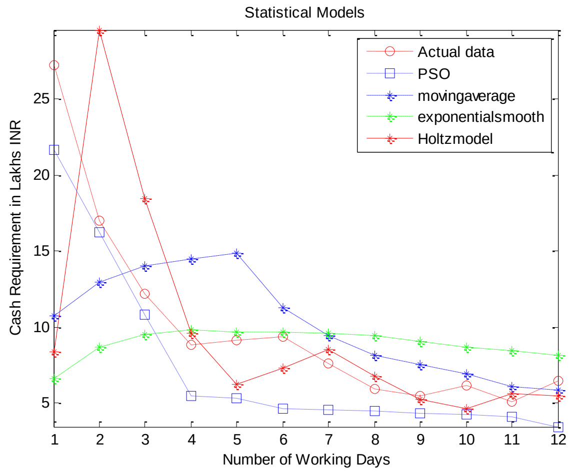

Figure 1.2: Cash Management Models

The performance MSE for the PSO and GSA data were 9.0678 and 15.9381 . The computational time for PSO for is 0.2911 seconds and GSA is 8.45 seconds respectively.

Table 1.2: Performance metrics - MAE, MAPE, MSE using PSO and GSA.

Model	Average MAE	Average MAPE	Average MSE
PSO	2.6011	29.1186	9.0678
GSA	2.7151	32.3300	15.9381

The accuracy of the proposed model helps to understand the influence of input parameters in the developed cash forecasting models with the better accuracy was shown in table 1.2. The efficiency of the cash forecasting model performed well was evident from the obtained results of PSO and GSA are tabulated in 1.2. It can be used for future cash forecasting of the bank and the technique proposed in this work can be implemented for finding the coefficients for any bank branch and their cash management.

The inference from the above Fig.1.2. shows the performance of statistical models and the same was compared with the actual data set. The above mentioned statistical models were normally used by the banks and micro financial organization to find the future cash requirement. Therefore the proposed method using PSO was compared and plotted in the Fig.1.2. It shows the difference between the actual , PSO, and the statistical models. The obtained results were plotted in Fig.1.1 and Fig.1.2 which shows the performance accuracy of PSO. The performance of moving average model ,exponential models and Holtz model are tabulated in table 1.3.

Table 1.3: Performance metrics MAE, MAPE and MSE for Statistical models

Model	Average MAE	Average MAPE	Average MSE
Moving Average	1.6728	12.1727	11.09618
Exponential	4.1565	17.2775	45.81849
Holtz	4.4708	12.066	61.428

The performance accuracy of proposed soft computing based PSO has the minimal MSE of 9.0678 is evident from table 1.2. The obtained results were compared and discussed to show the performance of PSO and GSA.

CONCLUSION

The PSO and GSA model was proposed to estimate the coefficients of cash management model . Based on the models developed and validated, the estimated results and observed data are in good agreement. The PSO gave better cash forecasting than GSA. It can be concluded that the cash management models using PSO is an efficient technique for parameter estimation and a promising candidate for the short term data. The optimized results were compared with the statistical models to prove the efficiency of the proposed models. It clearly depicts based on the achieved results, it was decided to use PSO for a coefficient selection of other models.

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