International Journal of Hybrid Information Technology
Vol. 9, No.10 (2016), pp. 325-334
http://dx.doi.org/10.14257/ijhit.2016.9.10.32

Forecasting Logistics Demand Using Unbiased GM (1,1) Model Optimized by AIWPSO Algorithm

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Abstract

Accurate forecast of logistics demand can provide scientific guidance for logistics planning and decision making. With the complexity and uncertainty characteristics in logistics demand, the forecasting of logistics demand shows comprehensive and complex. The forecasting precision of the traditional forecasting methods often are not satisfying. It is necessary to look for novel forecasting methods to enhance the forecasting precision of logistics demand. Integrating the unbiased GM (1,1) model (UGM (1,1)) into the adaptive inertia weight particle swarm optimization (AIWPSO) algorithm, this paper developed a novel model for forecasting logistics demand, called AIWPSO-UGM (1,1) model, in which the UGM (1,1) model was used to forecast logistics demand and the AIWPSO algorithm was adopted to optimize the grey parameters needed in UGM (1,1) model. Two examples were selected to prove the out-of-sample performance of the AIWPSO-UGM (1,1) model in forecasting logistics demand. The results imply that the proposed AIWPSO-UGM (1,1) model performs better in logistics demand forecasting compared to the GM (1,1) model optimized by AIWPSO algorithm (AIWPSO-GM (1,1)), UGM (1,1), and GM (1,1) models.

***Keywords**: Logistics demand forecasting, Unbiased GM (1,1) model, AIWPSO algorithm*

1. Introduction

Logistics demand forecasting is, based on historical data and market information, to analyze, estimate and infer the change regularity of logistics demand in the future by using appropriate methods and skills. There are various methods widely used for logistics demand forecasting, such as regression analysis [1], exponential smoothing method [2], time series analysis [3], elastic coefficient method [4], the rough set theory [5]. Logistics system is an uncertain system whose change is influenced by many factors, including the speed of development of national economy, the consumption level of residents and the impact of productivity layout. As a result, logistics demand sequence is characterized by nonlinearity and stochasticity. It is difficult for the traditional forecasting methods to reveal the uncertainty and complexity in logistics demand data, thus these forecasting methods can't obtain satisfactory forecasting precision.

Grey forecasting method is a key method of grey system [6]. It can weaken the stochastic and enhance the regularity of the original data by using unique data generation operation. And then constructs forecasting model based on the new data. GM (1,1) model is the most commonly used model composed of one first-order differential equation and a single variable. With the advantages of less number data required, simple calculation, and

ISSN: 1738-9968 IJHIT

high short-term forecasting precision, GM (1, 1) model is more suitable for logistics demand forecasting and has achieved good forecasting result [7-9]. On the other hand, Ji found that GM (1,1) model itself shows the inherent deviation due to its own theoretical reason. To solve this problem, he put forward an improved GM (1,1) model, called unbiased GM (1,1) model (UGM (1,1)). Unlike the traditional GM (1,1) model, UGM (1,1) model itself does not exist the inherent deviation [10]. Additionally, it was confirmed that the forecasting precision of UGM (1,1) model was superior to the traditional GM (1,1) model [11,12]. However, UGM (1,1) model presents the shortage in parameter solution algorithm that could impact the forecasting performance of UGM (1,1) model in a certain degree.

PSO algorithm is proposed by Kennedy and Eberhart in 1995. It is a kind of heuristic algorithm mimicking the social behavior of biological population [13]. Due to the good robustness and simple calculation procedure, PSO algorithm widely used in optimization problems. Adaptive inertia weight PSO (AIWPSO) algorithm is a reformation of PSO algorithm. By automatically changing the value of the inertia weight along with the fitness function, AIWPSO not only ensures the diversity of particles and the convergence of the algorithm, but also balances the global and local optimization ability [14].

In this paper, UGM (1,1) model is employed for forecasting logistics demand and AIWPSO algorithm is used to find the optimal parameters of UGM (1,1) model. The remaining sections of this paper are arranged as follows. Section 2 gives a brief introduction to UGM (1,1) model and AIWPSO algorithm, then the idea of UGM (1,1) model optimized by AIWPSO algorithm is described in detail and the steps of optimizing the grey parameters of UGM (1,1) model by AIWPSO algorithm is provided. Section 3 applies the proposed method to two examples and testifies the forecasting performance of the proposed method. Section 4 provides the conclusions.

2. Methodology

2.1. Unbiased GM (1, 1) Model

UGM (1, 1) model is an improved GM (1,1) model. It eliminates the inherent deviation of the traditional GM (1,1) model and expands the application scope. In additional, UGM (1,1) model doesn't need accumulated subtraction reduction, which can further improve the modeling efficiency.

Let $x^{(0)} = \{x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(n)\}$ be the original time series, with $x^{(0)}(t) \in R^{+}$, t=1,2,…,n. The new time series $x^{(1)} = \{x^{(1)}(1), x^{(1)}(2), \cdots, x^{(1)}(n)\}$is get by using the first-order accumulated generating operation (1-AGO), expressed as:

$$x^{(1)}(t) = \sum_{l=1}^{t} x^{(0)}(l),\ t = 1,2,\cdots,n \tag{1}$$

Then, the grey differential equation is established as follow:

$$\frac{dx^{(1)}}{dt} + ax^{(0)} = b \tag{2}$$

where a and b are grey parameters. The values of the grey parameters can be estimated by using the least squares method:

$$\left[\hat{a}, \hat{b}\right] = (C^T C)^{-1} C^T Y \tag{3}$$

where

$$C = \begin{bmatrix} -0.5\left[x^{(1)}(1) + x^{(2)}(2)\right] & 1 \\ \cdots & \cdots \\ -0.5\left[x^{(1)}(n-1) + x^{(1)}(n)\right] & 1 \end{bmatrix},\ Y = \left[x^{(0)}(2) \ \cdots \ x^{(0)}(n)\right] \tag{4}$$

After that, the parameters of UGM (1,1) model are calculated by the following formula:

$$A = 1n\frac{2-\hat{a}}{2+\hat{a}}, B = \frac{2\hat{b}}{2+\hat{a}} \tag{5}$$

Finally, UGM (1,1) model is set up using *A* and *B*, given by:

$$\begin{cases} \hat{x}^{(0)}(1) = x^{(0)}(1) \\ \hat{x}^{(0)}(t) = B \cdot e^{A(t-1)} \end{cases}, t = 2,3,\cdots,n \tag{6}$$

2.2. AIWPSO Algorithm

In the PSO algorithm, the inertia weight *w* is one of the important parameters. The value of *w* greatly affects the optimization performance of PSO algorithm. Adaptive inertia weight particle swarm optimization (AIWPSO) algorithm was proposed to improve the performance of PSO. The value of the *w* of AIWPSO algorithm updates dynamically with the change of the objective function, which overcomes the shortcomings founded in application of PSO algorithm, such as the "premature" and "oscillation" phenomena.

Assume a particle population encompassing *m* particles. Each particle searches for the optimal solution of the objective function (or called fitness function) in a *D*-dimensional space. The position and velocity vectors of the *i*th particle are $\boldsymbol{S}_i=(s_{i1}, s_{i2},\ldots, s_{iD})$ and $\boldsymbol{V}_i=(v_{i1}, v_{i2},\ldots, v_{iD})$, respectively. The position of each particle is a potential solution. The individual best position of each particle $\boldsymbol{P}_{ibest}=(p_{i1}, p_{i2},\ldots, p_{iD})$ and the global best position of the whole population $\boldsymbol{G}_{best}=(g_1, g_2,\ldots, g_D)$ are determined through the evaluation of each particle's fitness value. According to the following equations, each particle updates its own velocity and position:

$$V_i^{k+1} = w \cdot V_i^k + c_1 \cdot r_1 \cdot (P_{ibest}^k - S_i^k) + c_2 r_2 \cdot (G_{best} - S_i^k) \tag{7}$$

$$S_i^{k+1} = S_i^k + V_i^{k+1} \tag{8}$$

where V_i^k and S_i^k are the velocity and position at evolution generation number *k*, which are usually restricted as $\left|V_i^k\right| \le V_i^{\max}$ and $\left|S_i^k\right| \le S_i^{\max}$. And P_{ibest}^k , G_{best}^k are the individual best position and the global best position at evolution number *k*; c_1 , c_2 are acceleration coefficients used to adjust particle's own cognition and social components; r_1 , r_2 are two independent random number in the range of 0 and 1; *w* is the inertia weight which balances the local and global optimization performance. The *w* value is updated according to the fitness value, written as:

$$w = \begin{cases} w_{\min} - \dfrac{(w_{\max} - w_{\min}) \times (f - f_{\min})}{(f_{avg} - f_{\min})}, & f \le f_{avg} \\ w_{\max}, & f > f_{avg} \end{cases} \tag{9}$$

where w_{max} and w_{min} denote the maximal and minimal values of *w*, respectively. And *f* denotes the particle's current fitness value; f_{avg} , f_{min} denote the average and minimal fitness value of all particles.

2.3. The Optimal Unbiased GM (1, 1) by PSO

It is known from the process for constructing UGM (1,1) model that the grey parameters *a* and *b* are the key parameters in UGM (1,1). The values of these two parameters has directly impact on the forecasting ability of UGM (1,1) model. In the standard UGM (1,1) model, the least squares method (OLS) is used to estimate the grey parameters, which is the same as GM (1,1) model. OLS belongs to the linear regression method and the premise of application of OLS is that the logistics demand series must be normally distributed. If not, the estimators obtained are biased and non-consistent. However, the actual logistics demand series are random and nonlinear, with non-normal distribution. Accordingly, the estimators of the grey parameters by OLS shwo larger error, which will produce bad influence on the accuracy of UGM (1,1) model in forecasting logistics demand.

To enhance the performance of UGM (1,1) model in forecasting logistics demand, AIWPSO algorithm is applied to determine the grey parameters a and b needed in UGM (1,1) model. Specifically, each particle searches for the global optimal solution in the two-dimensional space composed of a and b. Taking the forecasting error as the fitness function, the particle swarm looks for the global best position based on the fitness function value. The steps of AIWPSO algorithm optimizing the grey parameters of UGM (1,1) model (AIWPSO-UGM (1,1)) for forecasting logistics demand are provided as follows.

Step1: Initialization of particle swarm. Initialize particle population size m. Give the parameters of AIWPSO algorithm, including the maximal evolution number k_{max}; the maximal and minimal inertia weight w_{max} , w_{min}; the acceleration coefficients c_1 and c_2. Randomly generate particle's position and velocity in the search space composed of (a, b). Set the upper bounds of position and velocity, respectively.

Step2: Definition of fitness function. Since parameter optimization is to improve the forecasting precision of UGM (1,1) model, the fitness function is defined as the mean square error:

$$F = \frac{1}{n}\sum_{t=1}^{n}(\hat{x}_t^{(0)}(t) - x_t^{(0)}(t))^2 \tag{10}$$

where $\hat{x}_t$ (t) , $x_t(t)$ represent the forecasted and actual logistics demand based on the estimating samples and n represents the number of estimating samples.

Step3: Evolution of particles. Set each particle's individual best position as the current position. Calculate the fitness value of each particle and take the minimal fitness value of particles as the original global best position. Update particle's velocity and position. Evaluate the fitness value of each particle and compare each particle's fitness value with its individual best position, if better, then update the individual best position. Compare the individual best position of each particle to the global best position, if better, update the global best position.

Step4: Judgment of stopping criterion. If the maximal evolution number k_{max} is satisfied, then stop the calculation. The global best position is corresponding to the optimal grey parameters (a^*, b^*), otherwise, go back to step 2.

Step5: Construction of UGM (1,1) model. Substitute the obtained optimal parameters (a^*, b^*) into the equation (5) and calculate the parameters A and B. UGM (1,1) model is constructed by using A and B. And then, the constructed UGM (1,1) model is used to forecast logistics demand.

3. Examples Analysis

3.1. Data Description

In this section, two examples, the logistics demand of China and of Hebei province, were analyzed to prove the forecasting performance of the proposed AIWPSO-UGM (1,1) model. The freight traffic volumes of China and of Hebei province were taken as the proxies of the logistics demand, respectively. The corresponding annual data are available from National Bureau of Statistics of China and Heibei Provincial Bureau of Statistics, spanning from 1990 to 2012.

Three other models are taken as the benchmarks to compare the logistics demand forecasting results of the AIWPSO-UGM (1,1) model using the same data. They are GM (1, 1) model optimized by AIWPSO algorithm (AIWPSO-GM (1,1) model), UGM (1,1) model, and GM (1,1) model.

3.2. Examples Process and Results Analysis

The whole logistics demand data for 23 samples was split into two groups: the estimating sample data for constructing the models, covering 10 samples and the forecasting sample data for testifying the models, covering 13 samples. The one-step-ahead rolling forecasting method was adopted to forecast the logistics demand. That is, the first 10 samples were used to forecast the logistics demand in the next period. Then, the sample data is rolled forward by adding a new sample and dropping the most distant one so that the sample length employed to forecast the logistics demand remain fixed. And the obtained new sample data with 10 samples length were again used to forecast the logistics demand of the next period. This process was repeatedly until the last period logistics demand was obtained.

In the AIWPSO-UGM (1,1) model, the parameters of AIWPSO algorithm were set as following: particle population size m=10; maximal evolution number k_{max}=20; maximal and minimal inertia weight w_{max}=0.9, w_{min}=0.1; acceleration coefficients c_1=2, c_2=2. Considering AIWPSO algorithm is a random searching algorithm and each optimization results may be biased in a certain range, the grey parameters of UGM (1,1) model were optimized twenty times continuously, the parameters corresponding to the minimal estimation error of UGM (1,1) model was selected as the optimal grey parameters (a^*, b^*). The UGM (1,1) model with the optimal grey parameters from AIWPSO algorithm was finally used to forecast the logistics demand.

To compare the performance of the four modeling in forecasting logistics demand, five statistics indices were selected, comprising the root mean squared error (RMSE), the mean absolute error (MAE), the heteroscedasticity-adjusted root mean squared error (HRMSE), the heteroscedasticity-adjusted mean absolute error (HMAE), and the theil statistic (THEIL). Table 1 and Table 2 list the five evaluation indices of the four models for forecasting logistics demand of China and of Hebei province.

Table 1. Evaluation Indices of the Four Models for Forecasting Logistics Demand of China

Indices	AIWPSO-UGM (1,1)	AIWPSO-GM (1,1)	UGM (1,1)	GM(1,1)
RMSE	647.5688	719.8612	1630.7133	1455.2448
MAE	509.6020	566.1442	1442.0192	1283.0115
HRMSE	0.0278	0.0303	0.0681	0.0633
HMAE	0.0235	0.0257	0.0614	0.0561
THEIL	0.0130	0.0145	0.0339	0.0301

Table 2. Evaluation Indices of the Four Models for Forecasting Logistics Demand of Hebei Province

Indices	AIWPSO-UGM (1,1)	AIWPSO-GM (1,1)	UGM (1,1)	GM (1,1)
RMSE	58.4894	118.2963	219.8710	193.3578
MAE	43.1070	81.3000	148.9726	131.5729
HRMSE	0.0510	0.0711	0.1220	0.1123
HMAE	0.0394	0.0580	0.0965	0.0885
THEIL	0.0223	0.0439	0.0889	0.0773

It is clear from Table 1 and Table 2 that for the two cases, the smallest values of RMSE, MAE, HRMSE, HMAE, and THEIL are appeared in the AIWPSO-UGM (1,1) model, which indicates that the AIWPSO-UGM (1,1) model achieves the best performance in logistics demand forecasting among the four models. The AIWPSO-GM (1,1) model produces smaller values of RMSE, MAE, HRMSE, HMAE, and THEIL compared to the UGM (1,1) and GM (1,1) models, showing a better forecasting performance in the AIWPSO-GM (1,1) model. As for UGM (1,1) and GM (1,1) models, the smaller values of the five evaluation indices are found in the latter. This means that the forecasting performance of UGM (1,1) model is superior to that of GM (1,1) model for the two cases.

Table 3 lists the forecasting results of the logistics demand of China using the four models. It is clear from Table 3 that in the forecast period, the maximal relative error value of the AIWPSO-UGM (1,1) model is only –4.86%, smaller than those of the other three models. The minimal relative error value of the AIWPSO-UGM (1,1) model is -0.02%, larger than that of GM (1,1) model but smaller than those of the AIWPSO-GM (1,1) and UGM (1,1)

Table 3. Results of the Four Models for Forecasting Logistics Demand of China

Year	Actual value	AIWPSO-UGM (1,1)		AIWPSO-GM (1,1)		UGM (1,1)		GM (1,1)	
		forecasts	Error (%)	forecasts	Error (%)	forecasts	Error (%)	forecasts	Error (%)
2000	13587	13098	-3.59	13083	-3.71	13913	2.40	13893	2.25
2001	14018	13693	-2.31	13681	-2.40	14052	0.24	14019	0.01
2002	14834	14114	**-4.86**	14091	**-5.01**	14248	-3.96	14222	-4.13
2003	15645	15188	-2.92	15126	-3.32	14746	-5.74	14731	-5.84
2004	17064	16547	-3.03	16514	-3.23	15514	-9.08	15515	-9.08
2005	18621	18802	0.98	18754	0.72	16807	**-9.74**	16845	-9.54
2006	20371	20856	2.38	19770	-2.95	18601	-8.69	18742	-8.00
2007	22758	22769	0.05	22769	0.05	20742	-8.86	20922	-8.07
2008	25859	25687	-0.67	25697	-0.63	23380	-9.59	23582	-8.81
2009	28252	29434	4.18	29542	4.57	26728	-5.39	27006	-4.41
2010	32418	31733	-2.11	31329	-3.36	30155	-6.98	30526	-5.84
2011	36970	36964	**-0.02**	36980	**0.03**	34611	-6.38	34999	-5.33
2012	41004	42401	3.41	42415	3.44	39877	-2.75	40334	-1.63

models. Apart from the relative errors in 2005 and 2007 from the AIWPSO-GM (1,1) model, in 2000 and 2001 from the UGM (1,1) and GM (1,1) models, the smaller relative errors are shown in the AIWPSO-GM (1,1) model.

Table 4. Results of the Four Models for Forecasting Logistics Demand of Hebei Province

Year	Actual value	AIWPSO-UGM (1,1)		AIWPSO-GM (1,1)		UGM (1,1)		GM (1,1)	
		forecasts	Error (%)	forecasts	Error (%)	forecasts	Error (%)	forecasts	Error (%)
2000	768	764	-0.60	766	**-0.31**	830	8.11	830	8.02
2001	808	767	-5.15	770	-4.72	822	**1.63**	820	**1.42**
2002	843	795	-5.67	793	-5.94	823	-2.39	821	-2.60
2003	806	830	3.05	836	3.76	828	2.75	826	2.55
2004	873	806	-7.60	805	-7.81	829	-4.96	829	-4.96
2005	913	850	-6.96	829	-9.27	861	-5.77	861	-5.75

2006	968	934	-3.48	934	-3.51	907	-6.29	908	-6.15
2007	1042	1027	-1.45	1019	-2.22	966	-7.30	968	-7.10
2008	1114	1122	0.77	1123	0.80	1041	-6.56	1043	-6.34
2009	1368	1207	**-11.81**	1205	-11.92	1126	-17.67	1130	-17.42
2010	1773	1737	-2.04	1736	-2.11	1316	**-25.80**	1325	**-25.25**
2011	2123	2073	-2.35	2413	**13.64**	1665	-21.60	1719	-19.04
2012	2429	2436	**0.28**	2656	9.36	2074	-14.62	2224	-8.43

Table 4 lists the forecasting results of the logistics demand of Hebei province using the four models. It is clear from Table 4 that during the forecast period, the maximal and minimal relative error values of the AIWPSO-UGM (1,1) model are 0.28% and -11.81%, respectively, smaller than ones of the other three models. With the exclusion of the relative errors of 2000 and 2001 from the AIWPSO-GM (1,1) model, of 2001 and 2002 from the UGM (1,1) and GM (1,1) models, the smaller relative errors are appeared in the AIWPSO-GM (1,1) model.

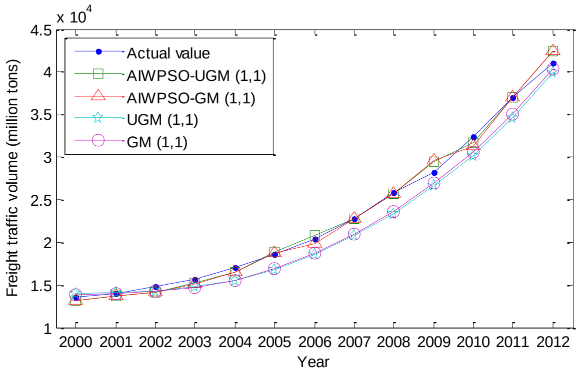

Figure 1. Comparison of the Forecasted and Actual Logistics Demand of China

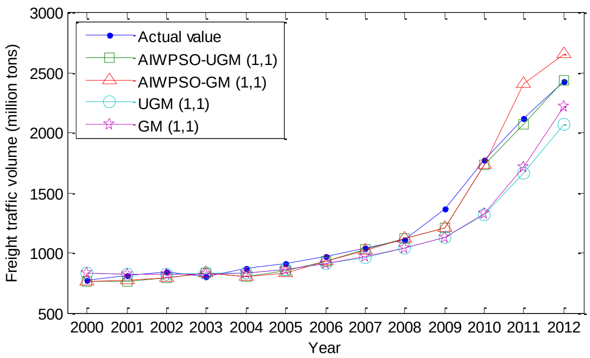

Figure 2. Comparison of the Forecasted and Actual Logistics Demand Of Hebei Province

Figure 1 and Figure 2 compare the actual logistics demand of China and of Hebei province with the corresponding out-of-sample forecasts with the AIWPSO-UGM (1,1), AIWPSO-GM (1,1), UGM (1,1), and GM (1,1) models. As shown in the two figures that for the two cases, all of the four models capture the increasing trending of logistics demand of China and Hebei province. Each of the forecast values of the AIWPSO-UGM (1,1) model is close to the actual values. While for the other three models, the forecast values of the early several years are close to the actual values and of the later several years are away from the actual values.

4. Conclusions

This paper provides an AIWPSO-UGM (1,1) model that combines UGM (1,1) model with AIWPSO algorithm for enhance the performance of the standard UGM (1,1) model in logistics demand forecasting. The UGM (1,1) model with the optimal parameter found by AIWPSO algorithm is utilized to forecast logistics demand. Two examples were analyzed to compare the effectiveness of the proposed AIWPSO-UGM (1,1) model with those of the other three models: AIWPSO-GM (1,1), UGM (1,1), and GM (1,1) models. The results indicate that the AIWPSO-UGM (1,1) model outperforms the other three models in forecasting logistics demand. As for the other three models, the AIWPSO-GM (1,1) model shows better forecasting ability than the UGM (1,1) and GM (1,1) models. And the forecasting performance of the GM (1,1) model is better than that of the GM (1,1) model.

Acknowledgements

This work is belongs to the Youth Talent Project of Colleges of Heibei Province “The research of intelligent combination forecasting methodologies for logistics demand based on the small sample data” (No. BJ2014097) and the Soft Science Project of Heibei Province “The research of regional logistics and regional economic coordinated development in Beijing, Tianjin and Heibei Province” (No. 15456106D).

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