EVOLVING WEIGHTS FOR A NEW U.K. DIVISIA

JANE BINNER
Aston University

QUN BO CHEN
University of Nottingham

GRAHAM KENDALL
University of Nottingham

Divisia money is a monetary aggregate that gives each component an assigned weight. We use an evolutionary neural network to calculate new Divisia weights for each component utilising the Bank of England monetary data for the U.K. We propose a new money aggregate using our newly derived weights to carry out quantitative inflation prediction. The results show that this new money aggregate has better inflation forecasting performance than the traditionally constructed Bank of England Divisia money.

1.Introduction

How money supply is measured is an important issue in economics as it has been used over recent decades for many purposes such as predicting movements in inflation and interest rates. A simple monetary aggregate construction uses a simple sum of the constituent monetary components. This method of aggregation (such as M4 in the UK) gives each component an equal weight disregarding the different monetary services they provide. This is considered to be inappropriate as these components are not perfect substitutes [1][4][7][13][17]. Divisia money has been proposed as it gives different weights to each component to reflect their different monetary services, [1][13][17]. Studies show that it is able to provide superior performance than simple sum, especially in short-term studies [13].

However, the calculation of Divisia weights can still be improved [3][5][7][13][17]. Artificial Neural Network (ANN) techniques have been used in order to establish if an improved Divisia formulation can be found by using the relationship between Divisia components and inflation as an experimental test bed[3][7][17]. The results show that a better prediction of inflation is possible with an ANN.

In most of the above works, ANNs are used to construct a direct relationship between Divisia components and inflation, without paying attention to the value of the Divisia weights. In this paper, we use an ANN to calculate the value of Divisia weights, and then construct a new ANN Divisia money aggregate, (ADM) to predict inflation. As this will assign an explicit value to each component weight, we may have more explicit information about regarding the relationship between these components in order to carry out econometric analysis.

We actually utilise Evolutionary Neural Networks (ENNs) due to their generalisation properties and the fact that less human intervention is required in order to establish key parameter values [11][18][20][21]. Compared with more conventional approaches to training neural networks, such as back-propagation, which have fixed architectures and the performance can be affected by the initial status of the network (for example, the number of hidden neurons, the initial weights, the activation function, the learning rate etc.), ENNs resolve these issues as they evolve both the connection weights and the architecture [3][6][22]. There are many applications where good results have been reported using evolutionary neural networks. For example, see [10].

The remainder of the paper is presented as follows: Section 2 gives a brief description of the evolutionary neural network methodology used in this paper. Section 3 presents the data we will use and the experimental setup. Section 4 shows the results, along with a brief discussion. The final section concludes the paper, in which we also provide some possible future research directions.

2. Evolutionary Artificial Neural Networks

A population based evolutionary network is used in this paper, where both the weights and architectures are evolved. All neural networks are fully connected and have only one hidden layer. The activation functions of the hidden and output neurons are sigmoid. The weights are evolved by using a (1+1) evolution strategy and the architectures are evolved by adding/deleting a hidden neuron.

The networks will have N inputs and N outputs (Figure 1). Hidden neurons are initially randomly chosen but cannot exceed N. All networks evolve their weights for a given number of iterations and then the half with better fitness are retained for the next generation. To create the half of the population that was killed off, we copy the half that survived. In this procedure, we add or delete a hidden neuron with the same probability. The superior one will be kept after comparing against its parent.

The fitness used to compare networks is not calculated directly from the network outputs. As we have $\boldsymbol{N}$ outputs in the output layer, each output represents the weight of each monetary component. The ANN-Divisia money (ADM) is then calculated and the annual monthly changes are used as the predicted inflation rate. The correlation coefficient value between this rate (X) and the real inflation rate (Y) is the fitness we use:

$$Cor\ (X;Y) = \frac{\sum x_i y_i}{\sqrt{\sum x_i^2}\sqrt{\sum y_i^2}} \quad \text{where } x_i = X_i - \overline{X};\ y_i = Y_i - \overline{Y}$$

Fitness values which are closer to 1 will be considered to be better. A fuller description of the above algorithm can be found in [6].

3. Data and Experimental Setup

3.1. *Data*

The actual inflation rate (IR) is calculated from Consumer Price Index (CPI), which is obtained from the Office for National Statistics[23] and seasonally adjusted in Eviews before it is used.

Seasonally adjusted Household sector Divisia data is used in this experiment, obtained from the Bank of England (BoE) statistical interactive database [24]. It includes 5 components: Notes & Coin (NC), Non-interest-bearing deposits (NIBD), Interest-bearing bank sight deposits (IBSD), Interest-bearing bank time deposits (IBTD), Building society deposits (BSD). In the BoE database, BSD has two components for household sector: Interest-bearing sight deposits Household sector and Interest-bearing time deposits Household sector. We simply add these two together to form our BSD data.

The start time t_s of the series and the end time t_e of the in-sample data set are chosen according to the data available in the BoE database, while the out-of-sample data set contains t_o time periods (months). So:

$$t_s = 31/\text{DEC}/1998 \text{ and } t_e = 31/\text{AUG}/2007 - t_o.$$

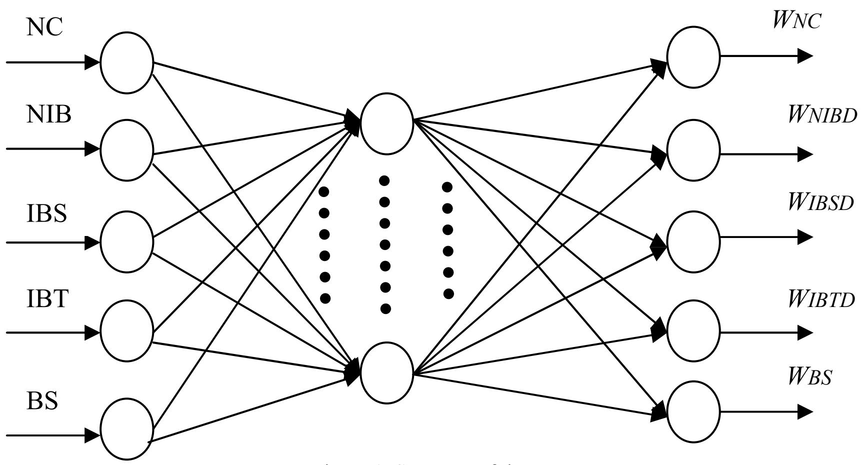

Figure 1. Structure of the ENN

3.2. *Experimental Setup*

When evolving the neural network on the in-sample data set, the outputs are the weight of each monetary component, as shown in figure 1. The ADM is calculated using the equation:

$$\begin{aligned} ADM[t] = NC[t] * W_{NC}[t] + NIBD[t] * W_{NIBD}[t] + IBSD[t] * W_{IBSD}[t] \\ + IBTD[t] * W_{IBTD}[t] + BSD[t] * W_{BSD}[t] \end{aligned} \quad (1)$$

Then the annual changes over ADM series are used as the new ADM inflation (ADMI) and the fitness of the network is the correlation between ADMI and IR, (where the correlation function is shown in section 2):

$$\text{Fitness(ANN)=Cor(ADMI}[t]\text{; IR}[t+ t_p]) \qquad (2)$$

As the model is used to predict inflation rate t_p periods ahead, IR's time range is always t_p periods ahead of ADMI's. To make all results for t_p comparable, we always predict 10 future inflation rates within the out-of-sample data set,. So $t_o = t_p +10$.

Only one network with the best prediction ability will be used as the final result. Here "best prediction ability" means that the fitness for Out-of-Sample data set is larger than other networks.

4. Results & Discussion

4.1 *Results*

In this experiment, we try to predict the inflation rate 1 to 12 months ahead (t_p =1…12) and compare it with the predicted inflation simply derived from BoE Divisia money (Household Sector only). Table 1 contains the fitness (correlation coefficient value) results for all time periods and data sets. Figure 2 shows the best result we get from ADM. As we are only concerned about the correlation of the two data series, Figure 2 is a tendency chart.

4.2 *Discussion*

From Table 1, we can see that all ADM in-sample correlation values are above 0.9, demonstrating that our ANN is effective. This is also shown in Figure 2, in which the general trend of predicted inflation rate of in-sample clearly follows the trend of the actual inflation rate (the vertical line is the end point of in-sample data). We only get good out-of-sample correlation values when t_p >4. If we only consider the single result for each t_p, this also indicates that better in-sample prediction does not mean a better out-of-sample correlation, especially when t_p =2. It has the best in-sample prediction but a worse out-of-sample prediction. However, from an economic viewpoint, this may indicate lag effects of monetary changes on inflation rates, as the predictions when t_p >4 are always good.

The correlation values of out-of-sample show that the ADM predictions perform much better than BoE Divisia predictions, especially when t_p >4.

Table 1: Correlations for ADM and BoE Divisia predictions with inflation

To Predict t_p Months Ahead	The ADM, Correlation Values			BoE Divisia, Correlation Values	
	Whole Series	In-Sample	Out-of-Sample	Out-of-Sample	Whole Series
t_p =1	0.904766	0.920896	-0.265	-0.40162	0.067774
t_p =2	0.913321	0.941649	-0.27085	-0.04694	0.047583
t_p =3	0.898422	0.929508	-0.5639	0.384374	0.024784
t_p =4	0.915511	0.93399	0.215899	0.520224	0.02202
t_p =5	0.901401	0.911897	0.715612	0.287942	0.015264
t_p =6	0.904616	0.914657	0.783388	0.341337	0.021752
t_p =7	0.904727	0.920627	0.804625	0.307459	0.014758
t_p =8	0.91948	0.936651	0.868571	-0.18326	0.009051
t_p =9	0.927175	0.922331	0.955497	-0.45024	0.000371
t_p =10	0.924101	0.915491	0.929802	-0.21714	0.025428
t_p =11	0.912052	0.902987	0.849114	0.224666	0.04061
t_p =12	0.861464	0.909664	0.725519	0.536843	0.037657

In Figure 2 (when t_p =9), we can see that in the out-of-sample data, the prediction line also follows the general trend of real inflation rate, especially at point A (the eighth point of out-of-sample data), this turning point is successfully predicted.

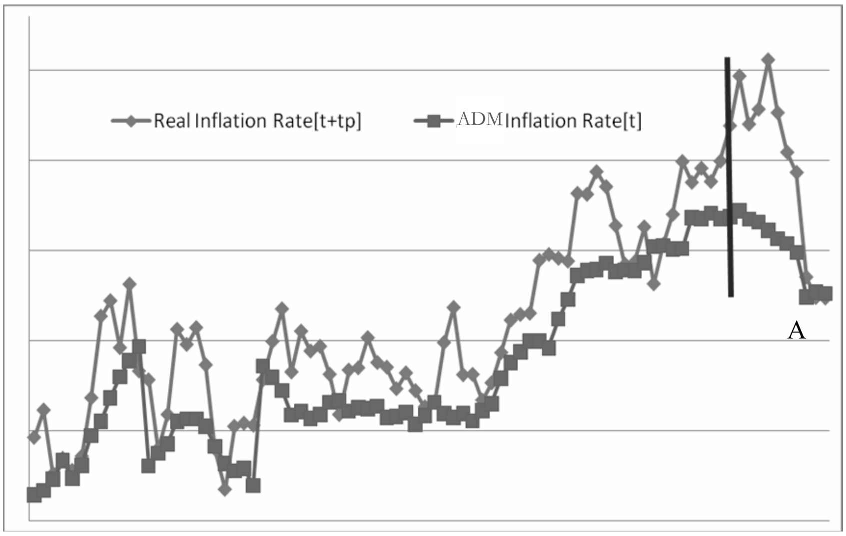

Figure 2: Inflation rates for t_p =9. Tendency only.

5. Conclusions

We calculate a set of weights for each Divisia monetary component by utilising evolutionary neural networks. The result shows that this new Divisia monetary aggregate performs significantly better than a simple sum aggregate when carrying out inflation prediction. It also shows that good in-sample predictions cannot guarantee good out-of-sample predictions. As the out-of-sample predictions are always better with increasing time lags, we note that although we do not consider some economic theories when setting up the experiment, these theories do emerge from our model, which may be useful for theoretical analysis.

This experiment only does simple quantitative analysis, when predicting the inflation rate, to avoid giving too much control to the weights we get from the ENN. In further studies, we would like to consider including more knowledge, data or theories to constrain these weights. Also, we use only monetary components as our inputs here. Taking the interest rates of them as additional inputs may also give even better results.

References

1. W.A. Barnett. *Journal of Econometrics,* **14** 11-48 (1980)
2. J. Binner, T. Elger, B. Nilsson and J. Tepper. *Advances in Econometrics*, **19** 71-92 (2004).
3. J. Binner, G. Kendall and A. Gazely. *idem*, **19** 127-43 (2004).
4. J. Binner, A. Fielding and A. Mullineux. *Applied Economics,* **31** 1021-31 (1999)
5. J. Binner, R. Bissoondeeal, T. Elger, A. Gazely and A. Mullineux. *idem,* **37** 665-680 (2005)
6. J. Binner, Q. Chen and G. Kendall. *International Conference on Computational Intelligence in Economics and Finance,* World Scientific Publishing Co. pp. 592-601, 2007 ISBN 978-981-270-967-7 (2007)
7. J. Binner, A. Gazely and S. Chen. *European Journal of Finance,* **8** 238-47 (2002)
8. K. Chellapilla and D. Fogel. *IEEE Proc. of Congress on Evolutionary Computation.* **2** 857-63 (2000)
9. L. Drake and T.C. Mills. *Economic Inquiry.* **43** 138-57 (2005)
10. D.B. Fogel, *Blondie24:Playing at the Edge of AI.*Morgan Kaufmann, (2001).
11. D.B. Fogel. *Evolutionary Computation: Towards a New Philosophy of Machine Intelligence-Second Edition.* IEEE Press, New York, (2000).
12. D.B. Fogel, Foundations of Evolutionary Computation, *Modeling and Simulation for Military Applications,*1-13, (2006).
13. M. Hancock. Bank of England Quarterly Bulletin, 45 39-46 (2005)
14. M.W. Hwang, J.Y. Choi, and J. Park, *IEEE Proceedings of International Conference on Evolutionary Computation,* 667–71 (1997).
15. Y. Liu & X. Yao, *idem.* 670–5 (1996).
16. S. Mirmirani and H.C. Li, *Advances in Econometrics,* **19** 203-24 (2004).
17. V. Schmidt and J. Binner. *idem,* **19** 225-241 (2004)
18. K.O. Stanley and R. Miikkulainen, *IEEE Proceedings of Congress on Evolutionary Computation,* 2 1757-62 (2002).
19. C. Tseng. *International Conference on Computational Intelligence in Economics and Finance,* (2006).
20. X. Yao, *Proceedings of the IEEE,* 87 [9] 1423-1447 (1999).
21. X. Yao and Y. Xu. *Journal of Computer Science and Technology,* 21 [1] 1-18 (2006).
22. X. Yao and Y. Liu. *IEEE Transactions on Neural Networks,* 8 [3] 694–713, (1997).
23. *http://www.statistics.gov.uk/statbase/tsdintro.asp*
24. *http://www.bankofengland.co.uk/statistics/index.htm*