Distributed Genetic and Eugenic Algorithms for Prediction of Gross Domestic Product Development by Frontal Neural Networks

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Abstract - The paper presents the possibility of application of frontal neural networks, distributed genetic algorithms and distributed eugenic algorithms in predicting of gross domestic product development by designing a prediction model whose accuracy is superior to the model used in praxis [1]. The learning process is implemented by means of a newly designed distributed algorithm based on the Eugenic Symbiotic Adaptive Neuro-Evolution (EuSANE) algorithm [2].

I. INTRODUCTION

The most commonly used models in the field of economic variables (EVs) prediction are models of time series extrapolation, single-equation regression models and multi-equation simultaneous models [3]. The models in each group are concerned with different complexity, design difficulty and degree of accuracy. Neural networks (NNs), genetic algorithms (GAs) [4,5] and eugenic algorithms (EuAs) [2,6,7,8,] provide in comparison with econometric methods of prediction the advantage of superior processing of non-linear dependencies [9] which may contribute to improvement of prediction accuracy [10]. Nominal gross domestic product (GDP) is one of the most complex indicators of production activity in the economy. Expected and actual development of GDP is among the crucial factors of determining state economic policy, making decisions about actual financial investments of corporations and households, drawing up corporate production budgets etc.

In the second section of this paper are introduce the index of leading economic indicators (ILEIs) and the diffusive index of leading economic indicators (DILEIs) of the US economy during the years 1965 - 2000. Up to now these indexes were not used for prediction of GDP. The third section of this paper contains the basic notions of frontal NNs with implicit presentation of time and basic notions of distributed genetic algorithms (DGAs) and distributed eugenic algorithms (DEuAs), which are used as learning algorithms for frontal NNs. The fourth section presents design the model of GDP prediction for the unconditional prediction of real GDP development of the USA on the basis frontal NNs. In the fifth section of this paper the learning process of the designed model on the basis of frontal NNs is realised by means of DGAs and DEuAs. A new learning algorithm for prediction model of GDP by means of frontal NNs was proposed on the basis of advantages of DGAs and DEuAs. The sixth section includes the analysis of results of designed model with new learning distributed EuSANE (DEuSANE) algorithm. A short conclusion of the results obtained in this paper and an overview of future research topics conclude the paper.

II. MODELLING OF GROSS DOMESTIC PRODUCT DEVELOPMENT

Even if business cycles are of different intensity, duration and are caused by various factors, there exist certain relations in the movement of EVs, which describe business cycles. Therefore, EVs used for the prediction of business cycles can be used for the prediction of GDP development. At the present time there are lots of EVs at disposal, which monitor the development of the economy, e.g. ILEI and DILEI.

The DILEI measures the percentage of decreasing and increasing EVs included in ILEI, i.e. the proportion of EVs indicating the reversal of economic growth. Both ILEI and DILEI can be used to model the prediction of GDP development. Both indexes are used in praxis for the prediction of recession. Whereas ILEI represents aggregate development of ten leading anti-cyclical EVs, DILEI measures the percentage of decreasing or increasing EVs, i.e. the proportion of EVs signalling the reversal of economic development. The interconnection of these two indicators provides a reliable signal of recession. It is assumed that recession starts if the average value of ILEI growth falls below 2 % and at the same time the value of DILEI drops below the critical value of 0.5. The existing econometric models of the prediction of GDP development use different formulations of relations among them and various methods of estimating the parameters of specified models. The presented facts result in different degrees of accuracy. The prediction accuracy can be described by means of average error ε, mean average error σ and root mean squared error δ.

III. NEURAL NETWORKS, GENETIC AND EUGENIC ALGORITHMS

The output signal of NN becomes a function of time when making the prediction. The time dimension can be implemented into NNs implicitly and explicitly. Time becomes the proper output signal with regard to the explicit in two ways, namely presentation of time. The implicit presentation of time represents the incorporation of the time dimension into the structure of NN. With regard to the implicit presentation of time, so-called filters [9], which apply short-term memory and operation of dimensional summation, can be used in feed-forward NNs. Dimensional summation represents the summing-up of input signals. Short-term memory preserves the knowledge about states of NN surrounding, ultimately about individual neurons in the close past. There exist several possible structures of short-term memory from which the most commonly used is memory with a constant number of delays. This type of memory works with discrete time and with the operation of delay z^{-b}, where b is the number of delay time intervals. This operation works in the way that for the value of variable x in time t the value of variable x in time t-b returns. Every memory has its depth measured by parameter b. Deeper memory means that more information about past states of surrounding is preserved.

As far as feed-forward NNs there exists two types of architecture with the implicit presentation of time, i.e. frontal NNs and distributed NNs. In frontal NNs short-term memory is situated in the beginning of NN as a fore-layer processing the time context. Classical back-propagation algorithms may learn such NNs or by another algorithm suitable for feed-forward NNs. Genetic algorithms are used as learning algorithms [4,5] of NNs. A GA can be expressed as follows [4,5]:

1. $\beta(t)$ = random-β( )
   /* Randomly initialise genotype population $\beta(t)$ */
   t := 0
   /* t is number of generation of GA */
2. Evaluation $\beta(t)$
   /* Assign fitness η to every genotype */
3. **DO WHILE** ($t < t_{max}$)
   /* Modify population of genotypes of $\beta(t)$ */
   p_s = probability-of-selection;
   p_c = probability-of-crossing;
   p_m = probability-of-mutation;
   c = position-of-crossing-cut;
4. Q := selection (p_s, η)
5. Q := crossing (p_c, c, η)
6. Q := mutation (p_m, η)
7. Evaluation Q
   /* Assign fitness η to every genotype */
8. R := smallest-η-genotype
   /* R are genotypes with the smallest fitness η */
9. $\beta(t+1) := (\beta(t) / R) \cup Q$
10. t :=t+1

   END

Genetic algorithms differ in the quality of epistasis processing. Epistasis represents the dependency of genotype fitness η on degree of interaction among alleles, eventually groups of alleles of genes. Epistasis occurs when a change of allele of a certain genotype or change of alleles of groups of genes causes an increase in the value of the objective function and at another time a decrease of this value, depending on alleles of other genes of the genotype. In this case it is not suitable to use GA, but the smart combination of alleles and groups of alleles is necessary. Eugenic algorithms enable the smart recombination dependent on the analysis of interaction among alleles and their groups [2,6,7,8].

Eugenic algorithms use principles of so-called eugenic evolution. Population develops according to the eugenic principles if genotypes with the smallest fitness η are gradually replaced by new genotypes generated on the basis of the smart recombination of genotypes of the entire population. Specific terms of algorithm are the smart recombination, the fitness φ of allele, the most significant gene, epistasis and population restriction [6,7,8].

The smart recombination represents the creation of new genotypes by the process of gradual assignment of alleles to genes of generated genotypes on the basis of explicit epistasis analysis. This means that EuA does not create new individuals by random crossing of suitable genotypes like GA, but by combining suitable alleles of genotypes. The selection of an allele of a certain genotype when constructing a new genotype depends on the fitness φ of this allele.

The fitness φ of an allele is measured as the average fitness η of all genotypes, which consists of a given allele in the existing population, eventually as the maximal fitness η of a genotype within all genotypes, which consists of a given allele. Assignment of alleles does not start from the first gene of a genotype when creating a new genotype, but from the most significant gene.

The most significant gene from the set of genes to which no allele has so far been assigned (the set of empty genes) is the gene with the greatest influence on the fitness η of the genotype. Basically, the change of the most significant gene causes the biggest change in the fitness η of the genotype. The degree of gene significance can be estimated on the basis of the numerical value of difference between the fitnesses φ of alleles, which the given gene may contain. If the difference between the fitness φ of certain alleles and alternative alleles is big for a given gene, the analysed gene becomes significant, because the change from certain alleles to alternative alleles will substantially change the fitness η of the entire genotype.

Epistasis indicates to what degree the best possible assignment of alleles of genes is dependent on already assigned alleles. The size of epistasis between assigned and unassigned alleles can be estimated on the basis of the biggest difference of probabilities of alternative alleles for given genes (D_{max}). Epistasis estimate can be calculated as $(1 - D_{max})$.

Population restriction enables a EuA to smartly combine suitable alleles, i.e. to solve epistatic problems. It occasionally happens when constructing a new individual that the significance of the next gene to which an allele should be assigned is so small that the choice of the correct allele is connected with great uncertainty because the fitness of alleles is very similar. A EuA reduces the degree of uncertainty in the sense that within population it concentrates only on relevant genotypes, which in the place of full genes consist of the same alleles that were so far assigned to new individuals. These genotypes form the population after the restriction. After the restriction of the population it is no longer worked out with the fitness φ of alleles, but with the conditional fitness φ of alleles, which is calculated as the average fitness η of subpopulation of relevant genotypes. Probability of the restriction of the population should be equal to the size of epistasis. A EuA can be, for example, expressed in the following way [2,6,7,8]:

1. $\beta(t)$ = random-β( )
   /* Randomly initialise genotype population $\beta(t)$ */
   L := 0
   /* L is number of new individuals created by EuA */

2. **DO WHILE** ($L < L_{max}$)
/* Create new individuals */
$G = \{ g_1, g_2, \dots ,g_l \}$
/* G is set of empty genes */
$\beta_r(t) = \beta(t)$
/* $\beta_r(t)$ is the population after the restriction */
3. **DO WHILE** Nonempty (G)
/* Select empty gene and assign allele to it */
4. g_g = the-most-significant-gene ($\beta_r(t)$, G)
5. $g_{g,a}$ = select-allele (g_g)
/* $g_{g,a}$ is allele assigned to g_g */
6. Remove g_g from G
/* Restrict the population if E is high */
7. E = epistasis-$\beta(t)$ ($\beta_r(t)$, G)
/* E is population epistasis of $\beta_r(t)$ */
8. p_r = probability-of-the-restriction (E)
9. **IF** (uniform-random [0,1] < p_r) **THEN**
10. $\beta_r(t)$ = restriction-$\beta(t)$ ($\beta_r(t)$, $g_{g,a}$)
END
/* Replace U by newly generated genotype */
11. U = the-most-unfitting-genotype ($\beta(t)$)
12. $\beta(t)_U = g$
13. L :=L+1
END

Distributed genetic algorithms (DEuAs) make used GAs (EuAs). Their task is to divide the population between define number of independent GAs (EuAs). All independent GAs (EuAs) works in a distributed system with the same task and with their own population (Fig. 1).

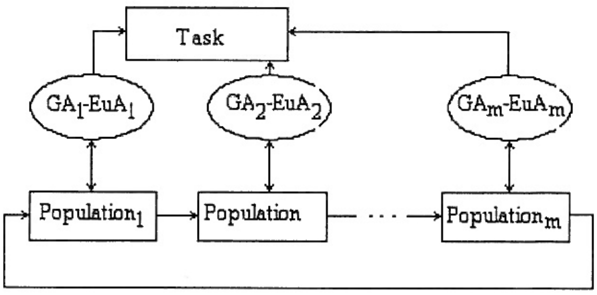

Fig. 1. Realization DGAs (DEuAs)

A DGAs (DEuAs) provides exchange of the population part between individual GAs (EuAs). Conditions of this exchange (the number of individuals, the method of choice of individuals, etc.) are predetermined by the user. The fitness η is evaluated at every GA (EuA) independently from the other GAs (EuAs). It enables to decrease the time consumption of the convergence towards the global maximum. The DGA (DEuA) can be expressed as follows:

1. Initialization: Let $t = 0$. Create m independent GAs (EuAs). For each GA (EuA) choose M_{max} individuals from a set of all possible genotypes and create populations $\beta_1(0),\beta_2(0), \dots ,\beta_m(0)$.
2. Generation updating: By means of genetic operators (selection, crossing, mutation) create from populations $\beta_1(t),\beta_2(t), \dots ,\beta_m(t)$ the following populations $\beta_1(t+1), \beta_2(t+1), \dots ,\beta_m(t+1)$. Then $t = t + 1$.
3. Choice of individuals: From each populations $\beta_1(t),\beta_2(t), \dots ,\beta_m(t)$ select M_v individuals with the highest fitness η and create sets $\beta'_1(t),\beta'_2(t), \dots ,\beta'_m(t)$, for which $\beta'_i(t) \subset \beta_i(t)$, $0 \le j \le m$.
4. Exchange of individuals: Insert the set $\beta'_i(t)$ into the population $\beta_{(i+1) \bmod m}(t)$.
5. Stop condition: If $t \ge t_{max}$, or the number of generations, the defined fitness η etc. is achieved, then stop DGA (DEuA); otherwise continue from the second step. Consider genotype $G_i \in \beta(t)$ with the highest fitness η the most suitable.

From analysis it follows that DGAs (DEuAs) obtain higher values of the fitness η. Distributed genetic algorithms (DEuAs) generally show better results than GAs (EuAs) except time consumption.

IV. THE MODEL OF GROSS DOMESTIC PRODUCT PREDICTION

The model of GDP prediction is designed for the unconditional prediction of real GDP development of the USA (which is expressed as percentage change of value of produced GDP against last quarter) whereas the moment of the prediction is 6 months before the beginning of the prediction period. The model of the prediction is presented by NN with the use of the filters applying short-term memory with a constant number of delays. The formulation of frontal NN [9,10,11,12] with the same memory depth of all filters, linear filter and linear output neuron is as follows:

$$Y = \sum_{k=1}^{K} \alpha_k d\left(\sum_{j=1}^{J} \beta_{jk} \sum_{i=1}^{b} \chi_{ijk} X_{ijk} \right),$$

where Y is the output of NN, α is synapse weight vector among neurons in the hidden layer and output neuron, β is synapse weight vector among filters and neurons in the hidden layers, χ is synapse weight vector inside the filter, k is index of neuron in the hidden layer, K is the number of neurons in the hidden layer, d is activation function, j is index of the filter, J is the number of filters per neuron in the hidden layer, b is short-term memory depth of the filter, X is the input vector of NN. Structures of the filter of frontal NN and frontal NN are shown in Fig. 2 and Fig. 3.

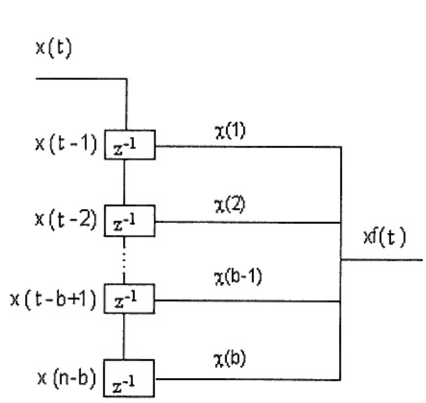

Fig. 2. The filter of frontal NN

Legend: x(t): the input value of the filter in time t, b: memory depth of the filter, χ: synapse weights within the filter, z^{-1}: operator of unit time delay, xf(t): the output of the filter for the input value in time t

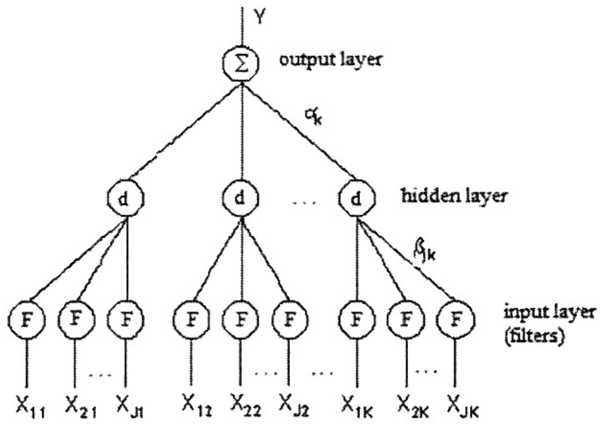

Fig. 3. Frontal NN

V. THE LEARNING PROCESS

The learning algorithm looks for such combinations of EVs, time delays and weights which lead to the least prediction error as regards tendency and size of GDP change. Thus the algorithm realises not only the prediction of GDP, but also the selection of suitable EVs, including time delays. The advantage of the proposed solution is the independence on the validity of statistical assumptions. In this case the space of all possible solutions consists of all possible combinations of EVs, their time delay and all synapse weights of NN. Considering that the required degree of accuracy is big, the first found local optimums of objective function will probably not be sufficient. Therefore, it is necessary to design the learning algorithm, which enables to leave local minimums and to continue to search in various segments of the space of all possible solutions. One of the suitable alternatives is the application of a DGA. A DGA can be considered as a faster algorithm than a DEuA, because a DGA does not compute epistasis. However, in this case epistasis analysis appears to be useful because of dependency of statistical significance of the additional EV of the model on the EV already included in the model, therefore application of the DEuA would be justified too. The DEuSANE algorithm, which allows taking advantage of both algorithms, obtain higher values of the fitness η. A new learning algorithm has been proposed for the model of frontal NN on the basis of advantages of the DEuSANE algorithm. Except for its presentation of neurons it differs from [2,6,7,8,11,12,13] in the sense that it does not work in two but in three grades. In the first grade the population of P0 filters associated with the input neurons is developed by means of a DGA. In the second grade the population of P1 neurons in the hidden layer is also developed by means of a DGA. In the third grade the population of P2 hidden layers is developed by means of a DEuA. This algorithm is shown (for the first two generations) in Fig. 4. The population initialisation of proposed DEuSANE algorithm is random. The end criterion of algorithm is the maximal number of the generations. Prediction quality should have two dimensions: deviation size of predicted value of GDP growth from real value and number of errors when predicting the tendency of GDP change. These criteria influence the construction of the objective function h. A suitable form is as follows:

$$h = \frac{1}{1 + O a_1} \; \frac{1}{1 + \delta a_2},$$

where O is the number of errors when predicting the tendency of GDP change, δ is the root mean squared error of the prediction, a is the parameter of the objective function. This function is maximised by means of the newly-designed DEuSANE algorithm to find the suitable economic hypothesis and the suitable parameter values of the prediction model. The aim goal of the algorithm is to find the combination of the independent variables and parameters of the model to obtain higher accuracy of the prediction in comparison with the Federal Reserve Bank of San Francisco (FRBSF) model [1].

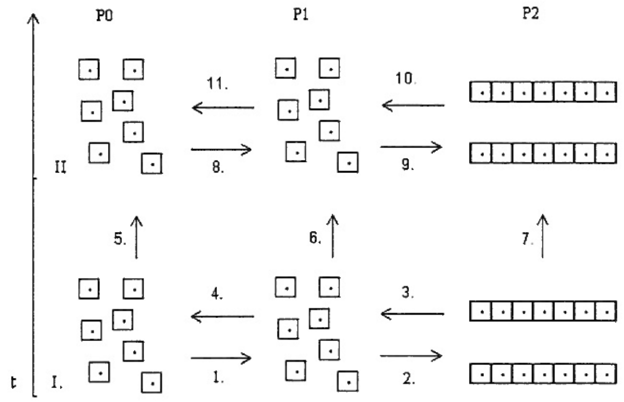

Fig. 4. Three-grade DEuSANE algorithm (first two generations)

Legend: P0: the population of the input neurons (filters), P1: the population of neurons in the hidden layer, P2: the population of the hidden layers, t: the number of the generation

1., 2., 8. and 9.: P1 consists of references to P0 and P2 consists of references to P1

3., 4., 10. and 11.: information about the fitness η of the hidden layers to calculate the fitness η of neurons in the hidden layer and information about the fitness η of neurons in the hidden layer to calculate the fitness η of the input neurons

5. and 6.: DGA

7.: DEuA

VI. ANALYSIS OF THE RESULTS

Development of frontal NN inputs in time [1] is shown in Fig. 5 and Fig. 6.

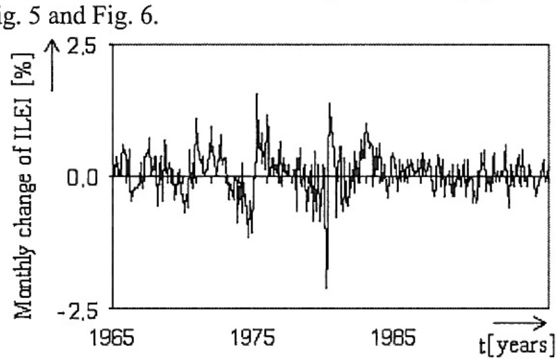

Fig. 5. Development of ILEI of the US economy in the years 1965 – 2000

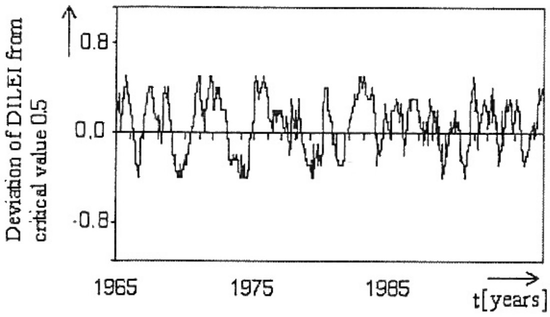

Fig. 6. Development of DILEI of the US economy in the years 1965 - 2000

Gross domestic product prediction is shown in Fig. 7. Parameters of the frontal NN model with one hidden layer, four neurons in the hidden layer, one filter per neuron in the hidden layer and different memory depth of the individual filters, inputs and synapse weights are presented in TABLE I.

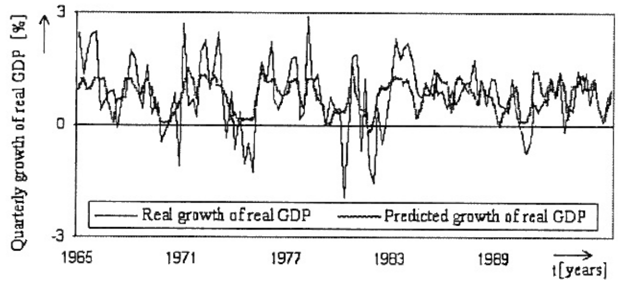

Fig. 7. Prediction of quarterly growth of real GDP by means of frontal NN

TABLE I Parameters of frontal NN

i	j	k	X_{ijk}	χ_{ijk}	β_{jk}	α_k
1	1	1	$ILEI_0$	-1.7122924		
	1	1			-2.9480438	
		1				1.045269
1	1	2	$ILEI_0$	-1.7122924		
	1	2			-2.9480438	
		2				-1.526722
1	1	3	$DILEI_0$	1.2792745		
2	1	3	$DILEI_{-1}$	0.7085032		
3	1	3	$DILEI_{-2}$	0.2784340		
4	1	3	$DILEI_{-3}$	-0.1060435		
	1	3			2.8213015	
		3				-1.89276
1	1	4	$DILEI_0$	1.2792745		
2	1	4	$DILEI_{-1}$	0.7085032		
3	1	4	$DILEI_{-2}$	0.2784340		
4	1	4	$DILEI_{-3}$	-0.1060435		
	1	4			2.8213015	
		4				3.67665

Legend: ILEI: growth of index of leading economic indicators against previous month in %, DILEI: deviation of diffuse index of leading economic indicators form critical value 0.5. Time delays of EVs are measured in months from the moment of the prediction, e.g. $ILEI_0$ is the value of ILEI at the moment of the prediction. The moment of the prediction is the end of the month at the end of the given quarter.

TABLE II consists of the average error values[1] of the prediction for the years of the learning set, testing set and for all years of prediction.

TABLE II Values of the average error indicators of frontal NN prediction

Indicator of the prediction error / Determination of time interval for which average error of the prediction is calculated	All years (1965-2000)	Learning set (1965-2000)	Testing set (1980-2000)	Years allowing comparison with FRBSF model (1985-2000)	Reference values of FRBSF model (1985-2000)
ε	0.0679	- 0.4313	0.4307	0.4555	approximately zero
σ	1.2815	1.1816	1.3751	0.8088	1.8451
δ	1.7738	1.6099	1.9148	1.1298	2.5111

It can be concluded on the basis of the data in Tab. II that a mean prediction error of approximately zero indicates the absence of systematic errors in the model. The value of indicator δ reveals the existence of several larger individual errors of the prediction. The proposed model achieves, within the indicator of mean errors, superior accuracy (with reference to the FRBSF model). Two times better accuracy was achieved by the designed frontal NN when taking into account the δ criterion, which puts emphasis on large individual deviations from the prediction. The size of individual errors for mean growth rates of GDP of the analysed model is shown in Fig. 8.

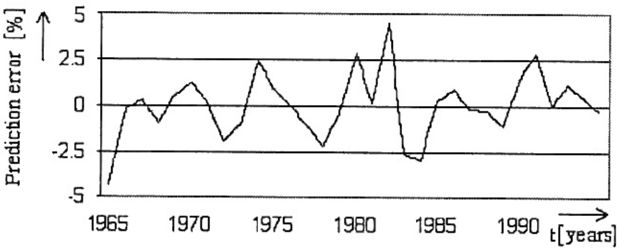

Fig. 8. Prediction error of frontal NNs for mean growth rates of GDP

From the results of Fig. 8 it may be seen that within thirty years of the prediction there occurred the predictions over 2.5% of yearly GDP, which are considered as high by monetary policy-markers. These are the predictions in the years 1965 (-4.29%), 1980 (-2.85%), 1982 (4.54%), 1984 (-3.03%) and 1991 (2.84%). Economic variables were problematic in the years 1981, 1982 and 1991. In these years the ILEI had insufficient explanation ability for the changes of GDP, because the group of EVs included in the given index did not consist of all-important EVs, which were connected with GDP development in selected years[2]. These

[1] Mean growth rates were obtained as yearly geometric averages of quarterly growth rates.

[2] Recession during the years 1981-82 was connected with restrictive monetary policy not only in the USA, but also in the countries of its business partners. However, the ILEI index does not take into account EVs describing development abroad. Recession in 1991 was connected with the sudden decline in household demand. Economic variables anticipating changes in aggregate demand are improperly involved in the ILEI index.

factors explain the prediction errors in the years 1981, 1982 and 1991. The prediction errors in 1965, 1974 and 1984 are connected either with the parameter estimates of the model or with the mathematical formulation of the model. From the analysis results that EVs and parameters of the model were found, which within given criteria provided superior accuracy of the prediction with reference to the FRBSF model. Development of the fitness η of the best genotype describing the swiftness of finding the parameters and inputs of final frontal NNs is shown in Fig. 9. This curve can be considered as the typical learning curve of the DEuSANE algorithm.

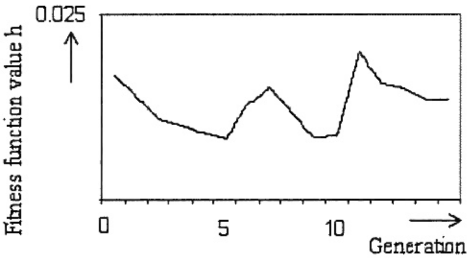

Fig. 9. Learning curve of DEuSANE algorithm

From the experiments, which were with the presented algorithm realized, results, those at majority of experiments (from 100) were most significant values of fitness achievement in first 15 generations. On the basis of experiments it is possible to observe high effectiveness of design three-grade DEuSANE algorithm. The presented results of the prediction of the GDP are presenting typical results of the experiments. The calculating time of the presented algorithm is in ordinal seconds units.

VII. CONCLUSION

The aim of the paper has been to show the possibilities of utilisation of frontal NNs, DGAs and DEuAs in the prediction of GDP development by designing a prediction model, which provides superior accuracy to the existing reference model. A model of GDP development formulated as frontal NN was designed to fulfil this goal, whereas parameter estimates and selection of EVs were realised by the newly-designed three-grade DEuSANE algorithm. Frontal NN uses the ILEI and DILEI as EVs of GDP development. This model was compared with the FRBSF prediction model used in praxis while mean error indicators of prediction were used as quality criteria. The model was designed by a combination of frontal NN, DGA and DEuA, which appeared to be more accurate within given criteria. On the other hand, the existence of several high individual errors limits the reliability of the proposed model. The existence of high individual prediction errors can be reduced by incorporating the given criteria into the objective function of the algorithm of the parameter estimates of the model. The fitness of application of the other activation function, which expresses the non-linearity type used to mathematically formulate relations between independent variables and dependent variable, can also be studied. Another way to improve the parameter estimates of the model is through application of the filter with a variable number of delays, eventually using the recurrent NN.

A software tool was developed for prediction of the GDP development. The software tool was developed in the C⁺⁺ programming language and run under Microsoft Windows.

VIII. ACKNOWLEDGEMENT

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IX. REFERENCES

[1] R. Ingenito and T. Bharat, "Using monthly data to predict quarterly output," *Federal Reserve Bank of San Francisco, Economic Review*, no.3, 1996, 9p.

[2] D. Polani and R. Miikkulainen, "Fast reinforcement learning through eugenic neuro-evolution," *Technical Report AI 99-277*, Artificial Intelligence Laboratory, The University of Texas at Austin, Texas, 1999.

[3] R. S. Pindyck and D. L. Rubinfeld, *Econometric Models and Economic Forecasts*, 4th edition, McGraw-Hill, Inc., Boston, 1998.

[4] J. H. Holland, *Adaptation in Natural and Artificial Systems*, University of Michigan Press, Ann Arbor, Michigan, 1975.

[5] V. Olej, "Evolution stochastic optimization algorithms: Genetic algorithms and evolution strategies," *Journal of Electrical Engineering*, vol.50, no.9-10, 1999, pp. 266-272.

[6] J. W. Prior, "Eugenic evolution for combinatorial optimization," *Report AI 98-268*, Artificial Intelligence Laboratory, The University of Texas at Austin, Texas, 1998.

[7] D. E. Moriarty and R. Miikkulainen, "Hierarchical evolution of neural networks," in *Proc. of the IEEE Conference on Evolutionary Computation*, ICEC-98, Anchorage, 1998.

[8] D. E. Moriarty and R. Miikkulainen, "Efficient reinforcement learning through symbiotic evolution," *Machine Learning*, no.22, 1996, pp.11-33.

[9] S. Haykin, *Neural Networks: A Comprehensive Foundation*, 2nd edition, Prentice-Hall, Inc., New York, 1999.

[10] G. Tkacz and S. Hu, "Forecasting GDP growth using artificial neural networks," *Working Paper 99-3*, Department of Monetary and Financial Analysis, Bank of Canada, Ottawa, Canada, 1999.

[11] V. Olej, „Prediction of gross domestic product development on the basis of frontal neural networks, genetic and eugenic algorithms,“ in *Proc. of the 2nd Euro-International Symposium on Computational Intelligence, E-ISCI 2002, Intelligent Technologies - Theory and Applications, New Trend in Intelligent Technologies,* IOS Press Ohmsha, Netherlands, 2002, pp.309-314.

[12] V. Olej, „Prediction of gross domestic product development on the basis of neural networks, genetic and eugenic algorithms,“ in *Proc. of the 8th International Conference on Soft Computing, MENDEL '2002*, Brno, Czech Republic, 2002, pp.153-158.

[13] V. Olej, *Modelling of Economics Processes on the Basis Computational Intelligence*, Miloš Vognar-M&V, Hradec Králové, Czech Republic, 2003.