SELF ORGANIZED CRITICAL DYNAMICS OF THE SUSTAINABLE DEVELOPMENT

by

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Meadows, Randers, and Meadows developed a computer model, which studied relations between global resources, production, and consumption. Their model solves a simple system of ordinary differential equations under different scenarios and predicts the future of variables like population, food production, and various measures of pollution and use of resources. Due to the complexities of the observed system, such a simple model can not take into account all significant parameters and therefore cannot be used for accurate long term predictions. Therefore we developed a neural network based model, which we tested with historical data to reproduce the Meadows results. We also used this model to cluster countries based on similarity as measured by the observed variables in an attempt to predict, which characteristics are most significant for their development.

Key words: sustainable development, neural networks, self organization

Introduction

Modeling of future development has become increasingly important in view of recent threats to global climate and social systems [1-4]. The objective of this paper is to test neural network [5] models as a possible tool for more accurate predictions of dynamics of sustainable development.

We have therefore started from the Meadows model of development [1, 2, 4], which predicts future values for several parameters ranging from economic to social and environmental for different scenarios, which depend on our decisions in the present [1]. We first test a neural network model with historical data to reproduce the Meadows model. Following this test we evaluate the proposed neural network model as a tool for better modeling of complex global social system. We use the neural network to cluster countries based on similarity of their development patterns, and to predict which characteristics are most significant for their development.

Model of Meadows

Meadows *et al.* [1] developed a system of ordinary differential equations, which describe the time dependence of observed parameters and their interdependence. They observe 45 different variables, which are connected with a set of 18 ordinary differential equations which describe the rate of change of 18 variables, 27 equations for the definition of other variables, and initial conditions which are given by historical data at the start of the observed period in year 1900. In their first version in 1972 historical data from 1900 to 1970 were used to fit the parameters of equations, and then the set of equations has been solved with a simple Euler or Runge Kutta type numerical method until the year 2100. First these equations have been solved with the assumption of business as usual, which means that no change in human behaviour would appear until 2100. Then several different changes have been proposed, and for each change the model parameters were slightly modified, and the set of equations was solved again. Different assumptions were used about variables like expected future nonrenewable resources, which depend on future discoveries and are difficult to predict, different levels of technological development, which are needed for reduction of pollution, extraction of nonrenewable resources and production of food, and different agreements on stabilization of population and industrial output. All the tested scenarios except one lead to more or less catastrophic outcome, which depletes natural resources and pollutes the environment, which further causes sharp drop in industrial output and food production, leading to hunger, poverty, and reduction of global population. The only scenario which can prevent such a disaster, requires a global agreement on stable population and stable industrial output as well as development of agricultural, environmental, and resource technologies. A more detailed description of this model and its results is given in reference 1.

After 30 years none of these alternative scenarios have been realised, though the world has been developing in the business as usual scenario. Nevertheless, the predicted catastrophic depletion of natural resources did not happen due to the technological advances which were not taken into account properly by this model. Therefore Meadows *et al.* [1] have updated their model and have taken into account the development until 2002 and calculated their model again. Then they solved the model for all scenarios, which were however slightly modified, *e. g.* instead of making the change in behaviour in 1972, the changes have been made in 2002. However, none of these changes described in the alternative scenarios seem to have been made until today, so that the world is still in the business as usual scenario. Meadows model predicts slowing down in growth of industrial output, food, and life expectancy, so that about 2015 they reach maximum and then they decline. As a consequence the global population also declines from the peak in about 2025.

Actual data since 2002 until 2008 show some oscillations in global food and industrial production. However growth is stable and no significant slowdown has been observed in spite of the large increase in the price of oil. While such oscillations depend on economic cycles, the predicted decline by the Meadows model is irreversible throughout the predicted period from 2015 until 2100.

Obviously the Meadows model has some significant deficiencies:

- it does not take into account oscillations due to economic cycles,
- it predicts slowdown in growth of industrial output, food and life expectancy, which have not been observed,
- it is in most cases irreversible, so that once the development changes into decline, this decline is permanent, and
- it does not take into account breakthrough discoveries in science and technology properly.

While these breakthrough discoveries are almost impossible to predict, it is certain that they will happen. The only way to estimate the effect of breakthrough discoveries is from historical data of developmental parameters. The challenge is that these breakthrough discoveries often change the observed system so significantly, that one must change the parameters used to describe the system and the relations between these parameters. While for example in the middle of 19th century the available whale oil was an important natural resource parameter, it is today almost insignificant. Similarly, development of new technologies is replacing the need for some raw material with another usually cheaper and more abundant. In order to take into account such unpredictable changes, we decided to use a neural network model in an attempt to elicit some further relations, which could describe development, but are difficult to get from oversimplified models such as the described Meadows model.

Verification of historical data with a neural network

Meadows *et al.* [1] presented several scenarios, which depend on our individual and collective behavior today and in the future. While these scenarios describe many different possibilities, current development doesn't closely resemble any of these scenarios. This is why we used another approach. We first trained a self organised mapping (SOM) neural network [5] system with historical data from Meadows between 1900 and 1970 in order to verify that the neural network can reproduce Meadows' results.

SOM neural network consists usually of a two or three-dimensional matrix of neurons, which are characterized with *n*-dimensional weight vectors \vec{W} . Training of the network with *n*-dimensional input vectors \vec{V} starts with random values of weight vectors. When an input vector is presented, we search for the neuron, whose weight vector has the smallest distance from the input vector. Then we change the old weights of this neuron \vec{W}_{old} and its neighbours into new weights:

$$\vec{W}_{new} = \vec{W}_{old} + \alpha (\vec{V} - \vec{W}_{old}), \tag{1}$$

where α is the learning coefficient, which is usually between 0 and 1.

After the network is trained, it can be used for classification of any *n*-dimensional input vector. Namely, the given input vector is compared with the weight of each neuron and a winning neuron is selected, which has the shortest distance between its weight and this input vector. Each input vector can thus be classified into a cluster, which is determined by the winning neuron, and this cluster is characterized by the weight vector of the winning neuron.

In this simulation we selected five parameters from Meadows model, namely population, natural resources, pollution, food, and industrial output, which are described in reference 1. We used a three dimensional 5 5 5 neural network, which we trained with historical data for these selected five parameters from 1900 until 1970 as 5-dimensional input vectors. When the network was trained, we plotted two-dimensional cross-sections of the obtained weight vectors (figs. 1 and 2). These plots demonstrate that the neural network can match the historical data by Meadows with less than 1% error.

An interesting question is what happens if the population increases above the values in figs. 1 and 2, which is the total population of about 4 billion as it was in 1970. In the next step we trained the same neural network with both historical and predicted values from 1900 until 2100 from 10 different Meadows scenarios [1]. From this simulation we present in figs. 3 and 4 the envelopes of the two-dimensional cross-sections of the obtained weight vectors. Also these results match the calculated results by Meadows to less than 1% error, which demonstrates that the network can learn quickly the patterns both from historical data as well as from predictions of Meadows' scenarios.

Although it is easier to solve this system of equations directly, the calculated solutions by our neural network model are significant, because they open new possibilities to model the observed complex system. Namely, the observed socio-economic system is so complex, that no reasonable finite set of variables connected by a system of differential equations could accurately describe its behaviour. While for instance natural resources could be described as a sum of all available minerals and fuels, their relative importance changes with the development of new



Figure 1. Neural network emerged pattern linking population and pollution as defined by Meadows, based on historical data from Meadows. Here pollution is measured in arbitrary units as defined by Meadows [1]



Figure 3. Neural network emerged pattern linking population and pollution as defined by Meadows, based on historical data and predictions from Meadows between 1900 and 2100 in 10 different scenarios [1]



Figure 2. Neural network emerged pattern linking population and industrial output as defined by Meadows, based on historical data from Meadows. Here industrial output is measured in arbitrary units as defined by Meadows [1]



Figure 4. Neural network emerged pattern linking population and industrial output as defined by Meadows, based on historical data and predictions from Meadows between 1900 and 2100 in 10 different scenarios [1]

technologies. For instance, the catalytic converters replaced the need for lead in gas with the need for platinum and similar metals for the production of catalytic converters. Similarly, invention of thin film solar cells replaced the need for silicon with tellurium and cadmium or with copper, indium, gallium, and selenium. As it is not possible to predict such scientific and technological breakthroughs, it is even in principle not possible to predict the need for natural resources in the long term future.

While the details of the observed system can not be predicted very accurately, mainly due to unknown scientific and technological breakthroughs in the future, it is possible to predict that such breakthroughs will occur and regularly change the relevance of individual system parameters. For such a rapidly changing system a neural network model should in principle be able

to make better predictions, because it can deduce more complex relations between the observed parameters, which are difficult to describe analytically in a system of differential equations. We therefore used the neural network to cluster the observed countries in a multidimensional space defined with the observed parameters.

Neural network model for classification

The Meadows model uses only global aggregate variables summed over all countries, and does not observe the situation in individual countries. In order to obtain more information about the critical parameters of development, we decided to expand the set of observed parameters to individual countries. Since it was not possible to obtain all the data used by Meadows for all countries at a reasonable quality, we decided to use only the data given in the World Factbook [6], namely 32 different parameters for each country: population, birth rate, death rate, Infant mortality rate, life expectancy at birth – total, total fertility rate, HIV/AIDS – adult prevalence rate, HIV/AIDS – people living with HIV/AIDS, HIV/AIDS – deaths, GDP (purchasing power parity), GDP – real growth rate, GDP – *per capita*, labor force, unemployment rate, inflation rate (consumer prices), investment (gross fixed), public debt, industrial production growth rate, electricity – consumption, oil – consumption, natural gas – consumption, exports, imports, debt – external, telephones – mobile cellular, internet users, airports, railways – total, roadways – total, waterways, merchant marine – total, and military expenditures – percent of GDP. These parameters are available for most countries. They are defined and listed in the World Factbook [6].

While these selected parameters differ slightly from parameters of Meadows, they cover main characteristics of each country reasonably well, so that the neural network can search for characteristic patterns. We have first normalized the values of each parameter to an interval from 0 to 1, where 0 would represent the minimum and 1 the maximum value of the observed parameter. We combined these normalized parameters into a 32-dimensional vector. From 233 countries described in the World Factbook we selected those 52 countries, for which all the data were available, and used these data as 32-dimensional input vectors to SOM neural network. We used a neural network composed of 48 neurons organized into a two-dimensional 8 6 matrix. We trained this network with input vectors for selected 52 countries. After training each of the 48 neurons represented one cluster characterized by its weight vector. Thirty of these clusters were populated by one or more countries, and 18 clusters were empty. A two-dimensional cross-section of these calculated 32-dimensional weight vectors with normalized population of each weight vectors on the horizontal axis and the normalized GDP-*per capita* on the vertical axis is shown in fig. 5. The names of investigated 52 countries are also given next to the point, which belongs to their cluster.

Discussion

We obtained some interesting indication. However at this stage it is premature to claim their conclusiveness. Nevertheless, these indications might offer some clues about the important variables, which stimulate the development, so we briefly discuss these findings.

While no cultural information about the countries was taken into account, the network surprisingly clustered together those countries, which seem to share some cultural similarities, so that for example:

(1) Baltic countries Estonia and Latvia form one cluster,

(2) African countries Gabon and Mozambique another,

(3) followed by an Eastern European cluster composed by Lithuania, Romania, and Ukraine,



Figure 5. Two-dimensional cross-section of the clusters obtained by the neural network with normalized population of each weight vectors on the horizontal axis and normalized GDP-*per capita* on the vertical axis. The names of investigated countries are given next to each cluster

- (4) a Central European Slavic one composed by Croatia, Poland, and Slovakia,
- (5) a Germanic cluster composed of Austria, Denmark, Ireland, Norway, Sweden, and Switzerland,
- (6) a cluster of superpowers United States and China,
- (7) former allies who abandoned their quest for military power Germany, Japan, and Italy,
- (8) a Central American one with Colombia and Ecuador and a surprising member Syria,
- (9) Greece and Republic Korea,
- (10) Egypt and the Philippines,
- (11) Malaysia and Mexico, and
- (12) Belgium, Canada, and the Netherlands.

These last 4 clusters are a bit more difficult to explain, and these countries may have ended in the same cluster by accident. Other countries were alone in their respective clusters. We realize that this clustering is not perfect, however it is surprising that such a simple process demonstrated connections between countries, which can not be deduced from the observed dataset in an obvious way.

Further, it was possible to demonstrate also relations between the calculated clusters, which are interesting in the discussion of relevant parameters for the development. Namely, a two-dimensional cross-section of these clusters in a 32-dimensional space given as a function of normalized population and normalized GDP-*per capita* of the cluster points clearly shows that most of the calculated clusters are distributed in three different curves (fig. 5):

- (1) from Denmark to USA,
- (2) from Spain and Portugal to Brazil, and
- (3) from Slovakia to Nigeria and India.

For all three curves GDP-*per capita* drops with increasing population. This might lead to a conclusion that smaller size of a country is more beneficial to its development. This conclusion is further supported by the fact that all top 4 countries with world highest GDP-*per capita* have less than one million people each, namely Qatar, Luxembourg, Bermuda, and Jersey, and that among top 12 countries only 4 have more than one million people, and of those 4 only 1 more than 5 million [6].

For the top curve GDP-*per capita* drops only slightly with the size of the country, for the middle curve GDP-*per capita* drops much faster with size, and for the bottom curve starts lower but drops more slowly than for the middle curve, so that both curves cross at the population of a few hundred million. While these curves are interesting as an indication that the level of development might depend on the size of a country, the distribution of countries among these curves is even more surprising. The top curve is composed of all the predominantly Germanic countries, Eastern Asian countries with old culture China and Japan, and Italy. Here Italy alone would actually be closer to the middle curve, however it is helped by its cluster partners Germany and Japan. The middle curve is composed of Brazil, the remaining European Romanic countries except Romania and the Asian tigers Republic Korea and Thailand. Eastern European, African, and other Asian and Latin American countries are on the bottom curve. We must however note that this distribution of countries into three groups is enhanced by the clustering process. Nevertheless, this result provides some interesting messages:

- the level of development of a country seems to depend on its cultural environment,
- the level of development seems to decrease with a larger size of the country's population,
- Germanic and traditional Asian cultures (Japanese and Chinese) seem to provide the best conditions for development,
- Romanic and some Eastern Asian cultures seem to provide next best conditions for development. Their level of development drops however much faster with increasing population. While this is not so good for large countries, the extrapolation toward small countries suggests that a small country of less than about one million might have better condition for development than even the countries in the top group. Unfortunately there were no countries small enough in our observed sample to test this hypothesis,
- most of the European countries in the top two groups either belong to the EU or are connected to the EU either through the European Economic Area or through bilateral treaties (Switzerland). Also, all the EU-15 countries except Finland, which were members of EU before 2004, are in the top two groups. Finland seems to be a special case as it does not fit to any of the observed three groups, although it is not far from the top group, and
- other countries seem to have more obstacles to development, and also here smaller countries are generally in a better position.

From the obtained results it might be possible to conclude that the road to development is in small country size, and the country being preferably connected into larger economic or geopolitical groups such as the EU. Well established traditional culture, such as Germanic, Romanic, Japanese or Chinese, is also beneficial. Here the type of the culture does not seem to be so important, as apparently very different Germanic and Japanese cultures lead to similar results, so apparently other factors are more important, and their determination would require further studies.

Conclusions

Obtained results demonstrate that self organized neural network can reconstruct historical as well as predicted data for the development parameters. The presented neural network model is therefore an interesting tool, which promises additional insight into the nature of development. A particular application of this neural network model demonstrates that it is able to create clusters of countries which indicate relations between the country's size and culture on one hand and its development on the other hand. While this study demonstrates that such relations can in principle be obtained, we did so far not get the results we aimed for, that is better future predictions than that of the Meadows model. Further studies could involve the time dependence and reveal more information and possibly identification of such pivotal parameters, which can have the most significant effect on sustainability of development and thus help to develop a comprehensive and holistic solution to prevent the collapse predicted by the Meadows model [1] and its negative social, environmental and economic consequences.

References

- [1] Meadows, D. H., Randers, J., Meadows, D. L., Limits to Growth: The 30-Year Update, Chelsea Green Publishing Company, New York, USA, 2004
- [2] Meadows, D. H., Randers, J., Meadows, D. L., Beyond the Limits: Confronting Global Collapse, Envisioning a Sustainable Future, Chelsea Green Publishing Company, New York, USA, 1993
- [3] ***, Climate Change, The Scientific Basis: Contribution of Working Group I to the Third Assessment Report of the IPCC (Intergovernmental Panel on Climate Change) (Ed. J. T. Houghton), Cambridge University Press, Cambridge, UK, 2001, see also: http://www.ipcc.ch/pub/reports.htm
- [4] Meadows, D. L., World3 Model, University of New Hampshire, Durham, N. C., USA, see also: http://www.unh.edu/ipssr/index.html
- [5] Lu, J., et al., Adaptive Networks, in Cognitive Networks: Towards Self-Aware Networks, (Ed. Qusay H. Mahmoud), John Wiley & Sons, West Sussex, UK, 2007
- [6] ***, Central Intelligence Agency, The 2008 World Factbook, Skyhorse Publishing, 2007, see also https://www.cia.gov/library/publications/the-world-factbook/, 2008

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