Advanced Learning of Fuzzy Cognitive Maps of Waste Management by Bacterial Algorithm

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Abstract – Fuzzy cognitive maps (FCMs) are a very convenient and simple tool for modeling complex systems. They are popular due to their simplicity and user friendliness. However, according to [1], human experts are subjective and can handle only relatively simple networks therefore there is an urgent need to develop methods for automated generation of FCM models. The present research deals with the methodology of FCMs in combination with the Bacterial Evolutionary Algorithm (BEA). The method of FCMs using BEA seems to be suitable to model such complex mechanisms as integrated municipal waste management (IMWM) systems. This paper is an attempt to assess the sustainability of the IMWM system by investigating the FCM methodology based on the BEA with a holistic approach. As a result, the best scenario to an IMWM system can be assigned.

I. INTRODUCTION

Waste management is one of the major environmental concerns in the world [2]. Sustainability is an essential goal for planning and natural resource management [3]. A system is sustainable if it is appropriate to the local conditions in which it operates, from a technical, social, economic, legal, institutional, and environmental perspective. In addition, if it is capable to maintain itself over time without reducing the resources needed. A system is integrated if it uses a range of inter-related collection and treatment options; involves all stakeholders; and takes into account interactions between the waste management system and other urban systems [4]. Realizing sustainable development, especially of the waste management sector is a challenge. Sustainable waste management means less reliance on landfill and greater amounts of recycling and composting. The waste management system consists of a whole set of activities related to handling, treating or recycling the waste materials. The purpose of waste management is to provide sanitary living conditions to reduce the amount of material that enters or leaves the society and encourage the reuse of material in the society [2]. For a waste management system to be sustainable, it needs to be environmentally effective, economically affordable and socially acceptable [5]. A typical IMWM system includes environmental, economic, social, institutional, legal and technical aspects. These factors are the ‘key drivers’ of a sustainable IMWM system that influence why the system operates as it does [4, 5, 6].

The modelling of complex systems requires new methods that can utilize the existing knowledge and human experience. These methods are equipped with sophisticated characteristics such as optimization, and identification qualities [7]. FCMs are an ideal tool for modelling multi-attribute systems, especially when they incorporate such ‘soft’ parameter as human factors, environmental characteristics or societal concepts [8].

Modern IMWM systems are complex and are inherently comprised of a large number of interacting components. These systems have nonlinear behavior and cannot simply be derived from summation of analyzed individual component behaviors [7]. In this application we were interested in investigating under what conditions an IMWM system may be sustainable.

This study aims to provide a method, which uses the BEA algorithm to develop FCM connection matrices based on historical data consisting of one sequence of state vectors. In contrast, some other methods introduced alternative approaches, which require a whole set of such sequences [1].

II. REVIEW OF THE METHODS USED

Fuzzy Cognitive Maps

FCMs are a soft computing methodology introduced by Kosko in 1986 [9]. FCMs are fuzzy graph structures for representing causal reasoning. Causality is represented as a fuzzy relation on causal concepts. FCMs are used for modeling dynamic systems [1]. The theory of FCM uses a symbolic representation for the description and modeling of the system. It utilizes concepts to illustrate different aspects in the behavior of the system, and these concepts interact with each other showing the dynamics of the system [10]. FCMs have been described as the combination of Neural Networks and Fuzzy Logic. Thus, learning techniques and algorithms can be borrowed and utilized in order to train FCM and adjust the weights of its interconnections [12]. The modeling of complex systems requires new methods that can utilize the existing knowledge and human experience [7]. It has become
quite clear that the requirements in modeling systems cannot be met by the existing conventional control theory and it is necessary to use new methods that will have learning capabilities and will be supplied with failure detection and identification qualities [7, 10]. The new theory for modeling IMWM systems we propose in this paper will contribute to realizing more sustainable IMWM systems. The new approach is called FCM with Bacterial Evolutionary Algorithm (BEA).

FCMs can be trained to lead a system to a desired state. Its adjustable character offers the ability to lead an FCM into a large set of different equilibrium state [11].

Bacterial Evolutionary Algorithm

In the late 1990s, Nawa and Furuhashi proposed a new evolutionary algorithm called the Bacterial Evolutionary Algorithm (BEA) [13, 14]. This algorithm was established as a further development of the already existing Pseudo-Bacterial Genetic Algorithm [15] and the classical Genetic Algorithm [16, 17]. The name of the algorithm indicates that its operation is similar to the process of the evolution of the bacteria. A possible solution of a problem is represented by the individual, which is often called bacterium as well. BEA keeps a record of all such bacteria called the bacterium population. Using the two main operators, bacterial mutation and gene transfer, it creates the successive generations of the population until some kind of termination condition is fulfilled. Finally, the best bacterium of the last generation is considered as a result.

III. METHODOLOGY

The model uses two different sets of input data. The sources of these two sets are different, one set is based on observations that may be considered more or less objective; observations on the trend of the studied factors in the time period from the 1980s till the 2020s. It is obvious that measuring the mutual influence of various factors within a complex phenomenon, like waste management is not easy. Nevertheless, it might be assumed that the time series published in the related literature [5, 6] is based on a consensus concerning the interrelationships of the concepts playing determinative roles in the procedure of waste management, thus these values are widely supported by independent observations and manually calculated partial models. In this research, the following data will be considered ‘objective’, even though they are not obtained by ‘measurements’ of some automatic machinery, but by the observation and evaluation of humans involved in the management of the procedure. It must be clearly understood that our learning model is based on these ‘objective’ data and there is no need to consult any experts in order to obtain up-to-date but entirely subjective data.

Nevertheless, in order to speed up the learning procedure, and to some extent, out of scientific curiosity, we collected a subjective set of data by sending out questionnaires where experts filling up the questionnaires were asked about their personal opinions regarding the estimated values and directions of pairwise influence among the six concepts on hand. Using this methodology, we gathered information from experts of integrated municipal waste management systems and this methodology will be used to extract the knowledge on the system of the experts and exploited their experience on the system’s model and behaviour. The aim of this survey was to establish the background database for the modelling of sustainability of IMWM systems.

It must be stressed that results of these questionnaires (which were compared, and the medium values selected for each matrix element as the typical ‘subjective’ value of the given influence) were used only as initial values for the learning procedure, under the assumption that starting with more or less realistic values would speed up the convergence of the matrix to the stable ‘objective’ values. Some comparative runs converged to these assumptions, even though convergence speed turned up to be quite high, thus it did not seem to be important which initial values were given when the learning procedure started.

It is nevertheless interesting to compare the ‘subjective’ mutual influence values obtained from the questionnaires and the ‘objective’ matrix obtained from the time series observed starting with the data from the 1980’s. On the basis of the gathered data we constructed the initial draft of the connection matrix, including identification of concept nodes and relationships among them that are represented by edges.

Simulation consists of computing the states of the system, which are described by a state vector, over a number of successive iterations. The state vector specifies current values of all concepts (nodes) in a particular iteration. The values of the given nodes are calculated from preceding iteration values of the nodes, which exert influence on the given node through cause-effect relationship. The transformation function is used to confine the weighted sum to a certain range, which is usually set to [0, 1]. The normalization hinders quantitative analysis, but allows for comparison between nodes, which are attached by fuzzy activity degrees defined as active (1), inactive (0) or active to a certain degree (values between 0 and 1) [1].

During the simulation process, the bacterial mutation creates new versions of bacteria with random modifications. With other words, this operator is liable for the exploration of the search space. The other operator, namely gene transfer, combines the genetic information of two bacteria. Thus it performs the exploitation of the genetic data. The operation of these operators is demonstrated by Figs. 1 and 2. Further details can be found in [13]. Some major benefits of the operators are that they realize elitism without additional computational effort, and the implementation of them is very straightforward.

The properties of the algorithm are very similar to the ones of other evolutionary algorithms. It cannot determine the exact solution of the examined problem; it only approximates the global optimum, but theoretically the probability of finding can be set arbitrarily large [18]. On the other side, BEA is able to optimise or solve complex problems even if they are not
continuous, noisy, high-dimensional, non-linear or multimodal.

Several researchers proposed new operators or modifications to improve the algorithm which are various Bacterial Memetic Algorithms [19, 20]. In these cases the main idea is to decrease the number of objective function evaluations using a local search algorithm (Levenberg-Marquardt) [21, 22]. Other researchers proposed modified gene transfer operators to allow parallel computation of the objective values [23].

During the optimisation of our FCM, forced mutation [24] was used to increase the otherwise very low value of genetic diversity, therefore to speed up computations. Forced mutation was applied in all subsequent generations after gene transfer. Below is the pseudo-code of the operator.

\[
\text{Loop for } i=2, \ldots, N
\]
\[
\text{Loop for } j=1, \ldots, i-1
\]
\[
\text{distance}=d(x[i], x[j])
\]
\[
\text{if distance}<\sigma:
\]
\[
\text{mutate } x[i]
\]
\[
\text{mark } x[i] \text{ for re-evaluation}
\]
\[
\text{jump out from inner loop}
\]
\[
\text{end if}
\]
\[
\text{End loop (j)}
\]
\[
\text{End loop (i)}
\]
\[
\text{Loop for } i=2, \ldots, N
\]
\[
\text{if } x[i] \text{ is marked for re-evaluation:}
\]
\[
\text{calculate } f(x[i])
\]
\[
\text{End loop (i)}
\]

\(x[i]\) denotes the \(i^{th}\) bacterium of the sorted population, thus \(f(x[i]) \leq f(x[i+1])\), where \(i=1,2,\ldots,N-1\). Here, \(f\) denotes the objective function, and \(N\) is the population size. The ‘mutation’ in the code uses Gaussian distribution to slightly modify the gene values if the bacteria are too similar to each other.

The value of \(\lambda\) used by the transformation function was represented with the first gene of the bacteria. The following 30 genes corresponded to the elements of the 6x6 connection matrix (the elements of the main diagonal were not stored).

IV. RESULTS

The goal of the experiment is to assess the sustainability of the IMWM system by investigating the FCM methodology based on the BEA with a holistic approach. First, the input data are presented, then the experience obtained during the simulation and finally the results are introduced. As it was mentioned beforehand, the model consists of two different input data. One is the expert system database which is based on human expert experience and knowledge. The source of the initial draft connection matrix is the gathered and averaged data which is shown in Table IA. It includes the identification of concept nodes and relationships among them, which are represented by edges.
The terms of concepts in the matrix are as follows: C1 – technical factor, C2 – environmental factor, C3 – economic factor, C4 – social factor, C5 – legal factor and C6 – institutional factor.

The above table is obviously not properly scaled. In order to obtain comparable values we normalized the connection values to the interval [0, 1]. As a result, the following matrix was obtained (Table IB).

The other input data set were the ranges of historical data consisting of two slightly different sequences of state vectors 1 and 2. Then two sequences of state vectors were calculated on the basis of the literature. One of them is a rude version (see Table II, Sequence of state vector 1), which shows the trend of the factors in a rough-and-ready way.

The other one is a refined version, which specifies more deeply the role of the factors according to changes in legislation, available techniques, social attribute, economic and institutional environment in time series (see Table III, Sequence of state vector 2).

With the input of the above data, the simulation was started. During the simulation, the program calculated two different FCM matrices. The method that is used to develop and construct the FCM has great importance for its potential to sufficiently model the system [9]. The proposed method is depending on the reliability of the input data. The simulation resulted in two different matrices according to the input sequence of state vectors 1 or 2. The resulted FCM matrices are presented in Table IV (based on sequence of state vector 1) and Table V (based on sequence of state vector 2).

The FCM determined the values of the concepts in the subsequent iterations using the connection matrix. The goal of using BEA was to find such a matrix that minimizes the difference between the real (see Table I) and the calculated values of the concepts. This difference \( d \) was expressed in Equation 1.
\[ d = \sum_{i=1}^{6} \left[ \hat{c}_i - c_i \right]^2 \]  

In Eq. 1, \([c_i]\) denotes the real and \(\hat{c}_i\) the calculated values of concepts.

The results of the optimization are: \(d_1 = 1.058\) and \(d_2 = 0.734\).

It is rather surprising how far the interrelation coefficients obtained by automatic learning (based on the more or less objective data of the time series observed) are from the coefficients calculated from the median of the experts’ questionnaires!

We have no doubt that the matrix obtained by learning is rather independent from subjective element, especially as it is resulting from data throughout a relatively long observation period. The fact that expert opinions differ so much from the objective reality definitely poses a question how deep the insight of waste management experts may be wherever a complex technical and social system consisting of several mutually influencing (and rather fluctuating) factors constitute the system on hand.

Despite the fact that a waste management system consists of only six main concepts, overviewing the whole procedure would need an approach based on the systems of systems concepts [25]. The latter approach stresses the problems of different type system components’ interoperability and interfacing which easily leads to unexpected emerging phenomena. The results obtained by the FCM model are unambiguously such emerging features that will necessarily lead to re-evaluation of the knowledge and views of environmental engineers dealing with waste management.

While in this approach we tried to find to optimize parameters with the help of the BEA and thus obtained a single set of results for the connection matrix in an alternative research [26] we found that results obtained with various, non-optimal steepness values \(\lambda\), the results were different essentially only in the scaling. After normalization, all estimated time series predictions converged to the same limit values.

V. SUMMARY

For large and complex system it is extremely difficult to describe the entire system by a precise mathematical model. (5). IMWM systems are real elements of our everyday life therefore problems generated from these systems are real problems.

From the unexpected results, from the fact that the mutual influence matrix obtained from the observation data is so thoroughly different from the matrix given by the experts that the obvious question comes whether the approach and the objective results are mathematically stable enough in terms of the uncertainty of the observed values.

In the near future, a sensitivity analysis of the method should be carried out.

It is also in evidence, that the program performed the simulation with different credibility. In case the input data correspond to reality, the method is suitable for simulating the problem and providing accurate results.

The speed and convergence of the learning method need to be investigated also by hybrid and combined evolutionary and memetic algorithms which were proven to be better than other simple algorithms.

ACKNOWLEDGMENT

The authors would like to thank to National Science Research Fund to grants OTKA K75711 and OTKA K105529, in addition Széchenyi István University for the support of the research.

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