ADRIENN BURUZS*, MIKLÓS. F. HATWÁGNER**, LÁSZLÓ T. KÓCZY***

MODELING INTEGRATED SUSTAINABLE WASTE MANAGEMENT SYSTEMS BY FUZZY COGNITIVE MAPS AND THE SYSTEM OF SYSTEMS CONCEPT

MODELOWANIE ZINTEGROWANYCH ZRÓWNOWAŻONYCH SYSTEMÓW GOSPODAROWANIA ODPADAMI ZA POMOCĄ ROZMYTYCH MAP POZNAWCZYCH ORAZ KONCEPCJI SYSTEMU SYSTEMÓW

Abstract

This paper describes the problems relating to the complexity of modern waste management systems. We present a new approach to selecting a better waste management solution. For a large and complex system it is extremely difficult to describe the entire system by a precise mathematical model. Therefore, we propose the use of Fuzzy Cognitive Maps (FCM), its combination with the Bacterial Evolutionary Algorithm (BEA) and the system of systems approach to support the planning and decision making process of integrated systems.

Keywords: *sustainability, integrated waste management system (IWMS), fuzzy cognitive map (FCM), bacterial evolutionary algorithm (BEA), system of systems (SoS) approach*

Streszczenie

W niniejszym artykule opisano problemy związane ze złożonością nowoczesnych systemów gospodarowania odpadami. Przedstawiono nowe podejście pozwalające na wybór lepszego rozwiązania gospodarki odpadami. W przypadku dużego i złożonego systemu, opisanie całego systemu za pomocą dokładnego modelu matematycznego przysparza ogromnych trudności. Stąd, w artykule zaproponowano użycie rozmytych map poznawczych oraz ich połączenia z bakteryjnymi algorytmami ewolucyjnymi, a także ujęcie systemu systemów w celu wspomagania procesu planowania i podejmowania decyzji w zintegrowanych systemach gospodarki odpadami.

Słowa kluczowe: *zrównoważony zintegrowany system gospodarki odpadami, rozmyte mapy poznawcze, bakteryjny algorytm ewolucyjny, ujęcie systemu systemów*

* M.Sc. Adrienn Buruzs, e-mail: buruzs.adrienn@freemail.hu, Department of Environmental Engineering, Faculty of Engineering, Széchenyi István University, Györ.
** Ph.D. Miklós. F. Hatwágner, Department of Information Technology, Faculty of Engineering, Széchenyi István University, Györ.
*** Prof. D.Sc. Ph.D. László T. Kóczy, Department of Automation, Faculty of Engineering Sciences, Széchenyi István University Györ; Department of Telecommunications and Media Informatics, Budapest University of Technology and Economics.

Symbols

V_k – the state k of the system
N – the matrix of the system which contains the weight ω_{ij}
$\lambda > 0$ – determines the steepness of the continuous function f

1. Introduction

Waste is one of the most visible environmental problems in the world [1]. Integrated waste management systems (IWMS) are real elements of our everyday life, therefore problems generated from these systems are real problems. The waste management system consists of a whole set of activities related to treating, transporting or recycling the waste materials. Waste management has evolved from the simple transportation of waste to landfills to complex systems, including several treatment and landfill techniques [2]. Modern waste management presents a high level of complexity. The purpose of waste management is to provide sanitary living conditions, to reduce the amount of materials that enters or leaves the society and to encourage the reuse of materials in the society [1].

Sustainability is an essential goal for the planning and management of natural resources. A system is sustainable if it is appropriate to the local conditions in which it operates from several perspectives. In addition, if it is capable to maintain itself over time without reducing the resources needed [3]. Sustainable waste management means less reliance on landfill and greater amounts of recycling and composting [1]. Sustainable IWMS should be environmentally efficient, economically affordable and socially acceptable [4], this way providing a comprehensive interdisciplinary framework for addressing all problems of managing urban solid waste. Realizing sustainable development, especially of the waste management sector, is therefore a great challenge.

Achieving sustainability in waste management requires an integrated approach. 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 [3]. Thus, the selection of a better waste management solution requires many aspects to be considered.

The rest of this paper is structured as follows. Section 2 describes the history and background of sustainable waste management and introduces the driving factors of the IWMS. (Hereinafter, in this paper the following expressions 'driving factors', 'key drivers' and 'concepts' have the same meeting; they stand for 'factors' that are the determining component of the waste management systems). Section 3 presents the methodological approach of the simulations by two Computational Intelligence tools: Fuzzy Cognitive Maps (FCM) and Bacterial Evolutionary Algorithms (BEA). Section 4 describes the results of the simulations. In chapter 5, we introduce the system of systems approach (SoS) and describe the basic subcomponents of the waste management system. Finally, a summary is given in Section 6 where future research intentions are described within the framework of SoS and the sustainability factors of waste management.

2. History and background

The IWMS has to be an economically affordable, environmentally effective and socially acceptable system. Among others, it includes the practical aspects of waste management (i.e. transport, treatment and disposal) and the attitudes of citizens (how they feel about source separation, recycling, incineration etc.). The evolution of waste management from truck and dump, to the highly integrated systems requires an investment of both time and resources [44].

Numerous studies introduce the history of waste management. According to [45], until the 1960s, municipal waste management was concentrated only on the collection and transportation of waste from households to the disposal facilities without any separation, which in the majority of cases, were local dumps or landfills. Processes were planned or optimised merely on the basis of efficiency in terms of costs. Environmental effects were only marginally taken into account. In the second phase, waste treatment and landfilling technologies were improved. After [46], in the 1970s, the goals of the municipal waste management systems were simply to optimize waste collection routes for vehicles or to locate appropriate transfer stations. In the 1980s, the focus was extended to encompass municipal waste management on a system level, minimizing the costs. This was the first time that the aspect of waste as a resource was taken into consideration. Complex waste management systems were first introduced and further developed from the 1980s onward. In the 1990s, specific treatment technologies for several types of waste were introduced, together with advanced landfill technologies [47]. With the transition from waste management to materials management, tools are needed that consider all aspects and effects of waste management [44].

In the preliminaries of this research, we investigated the conditions of sustainability of IWMS and determined its six driving factors. According to a general consensus in the literature these are the following: *environmental; economic; social; institutional; legal and technical* factors [3–8]. These factors are the 'key drivers' of a sustainable IWMS that influence why the system operates as it does.

In Table 1, the main factors and some examples of their respective subsystems are introduced.

We have accepted this approach as well-founded. However, some of the results of our present research motivate us to re-validate the inputs by the stakeholders in a later phase of the investigation. The level of modelling that is commonly presented in the relevant literature is not sufficient to determine the weight of each factor, therefore a more detailed approach to modeling is needed.

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

The modeling 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 [9]. It is obvious that uncertainties involved with waste management represent vagueness rather than probability. Fuzzy sets and fuzzy logic are suitable to construct a formal description and a mathematically manageable model of systems and processes with such uncertainties. Due to the incompleteness and multiple uncertainties occurring in sustainable waste management systems, we proposed

the use of FCM to support the planning and decision making process. By the observation of the model and its time dependent behavior, we can determine under what conditions the long-term sustainability of a regional waste management system could be ensured.

T a b l e 1

Factors of IWMS and their respective subsystems

Factors	Subsystem elements
Environmental factors	Emissions; Climate change; Land use; Recovery and recycling targets; Depletion of natural resources; Human toxicity
Economic factors	Efficiency at subsystem level; Efficiency at system level; Available funding/subsidies; Equity; System costs and revenues; Pricing system for waste services, Secondary materials market
Social factors	Public opinion; Public participation in the decision making process; Risk perception; Employment; Local demographics – population density, household size and household income; Public resistance (NIMBY – Not In My BackYard, LULU – Locally Unacceptable Land Use)
Institutional factors	Local and regional politics and planning; Managerial conditions and future directions; Institutional and administrative structure of waste management
Legal factors	Relevant legislation (international, national, regional and municipal)
Technical factors	Collection and transfer system; Treatment technologies; Waste stream composition and change

FCM is an ideal tool for modeling multi-attribute systems, especially when they incorporate such 'soft' parameter as human factors, environmental characteristics or societal concepts [10]. Our goal was to develop an objective, state-of-the-art model and 'tool kit' that could be used to take highly informed and focused decisions regarding sustainable integrated solid waste management on a regional level.

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.The goal of the simulation was to assess the sustainability of the IWMS by investigating the FCM methodology applying the BEA with a holistic approach [11, 12].

3. Methodological Approach

In the next two subchapters the applied Computational Intelligence tool kit will be briefly described.

FCM is a very convenient and simple tool for modelling complex systems. It is rather popular due to its simplicity and user friendliness. Its one disadvantage is that it is not able to extrapolate properly from the available time series data, it always converges to a set of

'plateaus', i.e. an assumed stable state. The present research deploys the FCM and applies the BEA for parameter optimization.

3.1. Fuzzy Cognitive Map

On the basis of a FCM's development, during the first step in the design process, the number and features of concepts are determined by a group of experts. After the identification of the main factors affecting the topic under investigation, each stakeholder is asked to describe the existence and type of the causal relationships among these factors and then assesses the strength of these causal relationships using a predetermined scale, capable of describing any kind of relationship between two factors, positive and negative.

Starting from the primary elements of a FCM, the *i*-th concept denotes a state, a procedure, an event, a variable or an input of the system and is represented by C_i ($i = 1, 2, ..., n$). Another component of a FCM is the directed edge which connects the concepts *i* and *j*. Each edge includes a weight w_{ij} which represents the causality between concepts C_i and C_j. The values of the concepts are within the range [0, 1], while the values of the weights belong to the interval [−1, 1]. A positive value of the weight w_{ij} indicates that an increase (decrease) in the value of concept C_i results to an increment (decrement) of the concept's value C_j. Similarly, a negative weight w_{ij} indicates that an increase (decrease) in the value of concept C_i results in a decrement (increment) of the concept's value C_j, while a zero weight denotes the absence of a relationship between C_i and C_j (Fig. 1). Considering the interrelations between the concepts of a FCM, the corresponding adjacency matrix can easily be formed.

Usually, it is accepted that causality is not self reflexive, i.e., a concept cannot cause itself, which means that the weight matrix always has '0-s' in its diagonal [48]. Otherwise the component would grow without limits.

The description of the inference mechanism, which represents the behaviour of the physical system, lies in the interpretation of FCM's mathematical formulation. After the initialization of the FCM and the determination of concept activation values by experts, concepts are ready to interact. As is obvious, the activation of a concept influences the values of concepts that are connected to it. At each step of interaction (simulation step), every concept acquires a new value that is calculated according to equations (Equation 1 and 2) and the interaction between concepts continues until fixed equilibrium is reached, a limit cycle is reached, or a chaotic behaviour is observed [49].

The mathematical description of our FCM system is a simple loop:

$$V_{k+1} = f(N \cdot V_k) \tag{1}$$

where:

V_k – the state *k* of the system,

N – the matrix of the system which contains the weight $w_{i,j}$, and

$$f(x) = \frac{1}{1 + e^{-\lambda x}} \tag{2}$$

where $\lambda > 0$ determines the steepness of the of the continuous function *f*.

Several models have been developed in recent decades to support decision making in IWMS to monitor present conditions, to assess future risks and to visualize alternative futures [13, 14]. Many environmental problems would benefit from models based on the experts' knowledge [15], among them IWMS modelling as well. The methodology extracts the knowledge from the stakeholders and exploits their experience of the system's model and behaviour.

In the development of the FCM, in the first step of the design process, the number and features of the constituting factors were determined by the relevant literature, as it was mentioned beforehand. These factors are supposed to be combined together in a single system, with mutual interactions. We have conducted an online survey where each one of the stakeholders was asked to describe the existence and type of the causal relationships among the six concepts and then to assess the strength of these using a predetermined simple scale, capable of describing any kind of relationship between a pair of factors, both positive and negative. Thus, from each interviewee, theoretically, a different hypothetical FCM could be established. As a positive aspect of this study, we have to notice that the participants were highly motivated to take part in the survey process without the need to understand the mathematical background of the methodology.

The 75 individual maps were however, merged into a representative, collective map. In this phase, we were primarily interested in investigating how the stakeholders perceived the future prospects of the IWMS.

FCMs are fuzzy graph structures representing causal reasoning. Causality is represented here as a fuzzy relation of causal concepts. FCM may be used for the dynamic modelling of systems. The FCM approach uses nodes corresponding to the factors and edges for their interactions, to model different aspects in the behaviour of the system. These factors interact with each other in the FCM simulation, presenting the dynamics of the original system [16]. 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 the FCM and adjust the weights of its interconnections [17].

3.2. The Bacterial Evolutionary Algorithm

In order to optimise the FCM-based model, the BEA was chosen because our previous experiences and results with various benchmark data sets revealed that BEA and Bacterial Memetic Algorithms (BMA) were among the most efficient evolutionary algorithms [18, 19]. This was especially true for the variants equipped with the most appropriate and suitable operators (see below). Several papers presented comparisons of these algorithms with other evolutionary and population based heuristics, e.g. when the goal was fuzzy rule-based learning of various physical models [19, 20], or when the Permutation Flow Shop Problem had to be optimised under certain conditions [21, 22].

The BEA was originally proposed by Nawa and Furuhashi in the late 1990s as a new evolutionary algorithm [23, 24]. This algorithm was established as a further development of the already existing Pseudo-Bacterial Genetic Algorithm [25] and the classical Genetic Algorithm itself [26, 27]. The name of the algorithm indicates that its operations are similar to the process of the evolution of bacteria. A possible solution of a problem is represented by an individual bacterium. The BEA keeps a record of all available bacteria, i.e., solutions, called the bacterium population. Using the two main operators, bacterial mutation and gene

transfer, it creates successive generations of the population until some kind of termination condition is fulfilled. Finally, the best bacterium of the last generation is considered as the result, i.e., the best approximation of the optimal solution. During the simulation process, the bacterial mutation creates new versions of bacteria with random modifications. In other words, this operator is liable for the exploration of the search space. Depending on some parameters governing the spread or deviation of the mutation results, its properties balance between 'globalness' and convergence speed. The other operator, namely gene transfer, combines the genetic information of pairs of bacteria. Thus it performs the exploitation of the genetic data. Further details can be found e.g. in [28].

Some major benefits of the operators are that they realize elitism without additional computational efforts, and the implementation of them is very straightforward. The properties of the algorithm are similar to the ones of other evolutionary algorithms, even though our experience shows that for most types of problems, it provides better approximation and convergence than the others. It cannot typically determine the exact solution of the examined problem, however, it approximates the global optimum. Theoretically, the accuracy might be arbitrarily good and the probability of finding the exact optimum in discrete problems might be arbitrarily large [29]. 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 BMAs [30, 31]. In these cases, the main idea is to decrease the number of objective function evaluations using a local search algorithm (e.g. the rather efficient, but also rather complicated, Levenberg-Marquardt algorithm) [32, 33]. Other researchers proposed modified gene transfer operators to allow parallel computation of the objective values [34].

In the literature, there are some references provide which a good overview on the soft computing tools [50–52].

4. Results

In the first simulation, our starting point was a fixed connection matrix. In this approach, we studied the changes of the importance values of the factors over time.

The second experiment was about parameter identification using BEA. The connection matrix of FCM was determined so that the difference between the original time series of concepts given in literature and the generated ones using this matrix should be as small as possible.

4.1. Results with the FCM Simulation

The goal of this first experiment [35] was to assess the sustainability of the IWMS by investigating the FCM methodology with a holistic approach. First, the input data, then the experience obtained during the simulation are presented and finally, the results are introduced.

The model consists of the expert system database which is based on human expert experience and knowledge obtained from the questionnaires. Namely, the initial draft connection matrix is the data gathered and averaged from the survey process shown in Table 2. This model includes the identification of concept nodes and the relationships among them, these are represented by edges.

Table 2

The initial draft of the connection matrix

	C1	C2	C3	C4	C5	C6
C1	0	0.8	0.6	0.6	0.4	0.4
C2	0.6	0	0.6	0.6	0.4	0.4
C3	0.8	0.6	0	0.6	0.4	0.4
C4	0.4	0.6	0.4	0	0.4	0.4
C5	0.6	0.6	0.4	0.6	0	0.6
C6	0.4	0.4	0.4	0.4	0.4	0

The factors in the matrix are represented as follows:
– C1 – technical factor;
– C2 – environmental factor;
– C3 – economic factor;
– C4 – social factor;
– C5 – legal factor;
– C6 – institutional factor.

The other input data set was the range of historical data consisting of sequences of the state vectors. According to [2–9], the trend of the studied factors was assessed by values between 0 and 1 from the 1980s to the 2010s. The sequences of the state vector were designed on the basis of the literature and therefore it may be assumed that they soundly specify the role of the factors according to changes in the legislation, the available techniques, the social attitude, and the economic and institutional environment, as a time series (see Table 3, columns t_0–t_4).

Table 3

The sequences of the state vectors

	t_0	t_1	t_2	t_3	t_4	FCM averages
Technical	0.20	0.35	0.60	0.75	0.80	0.80
Environmental	0.15	0.20	0.40	0.60	0.80	0.71
Economic	0.10	0.15	0.30	0.50	0.70	0.62
Social	0.10	0.15	0.20	0.40	0.60	0.56
Legal	0.10	0.30	0.50	0.70	0.80	0.71
Institutional	0.10	0.20	0.30	0.50	0.60	0.58

Unfortunately, the number of available data is very small. From the literature on waste management modelling, only such a small amount of the data can be acquired.

FCM uses fuzzy values to represent the states of factors (concepts) in different moments (time series data) and to describe the strength of connections between the factors.

During the simulation, we determined different values for λ in order to see how the parameter influenced the results of the simulation. The simulation was always started with the input of the above data. The simulation resulted in different iterations according to the value of λ. We scaled the initial state of the system in the [0, 1] interval and we used this model and ran the simulation for 10 iteration cycles. The results are presented below.

From Fig. 1, it can be observed that the system converges to an equilibrium state which is robust to the initial state variation, however, the value of λ is different in each simulation. The estimated optimal value of λ may be determined by comparing the obtained results with the expert system database.
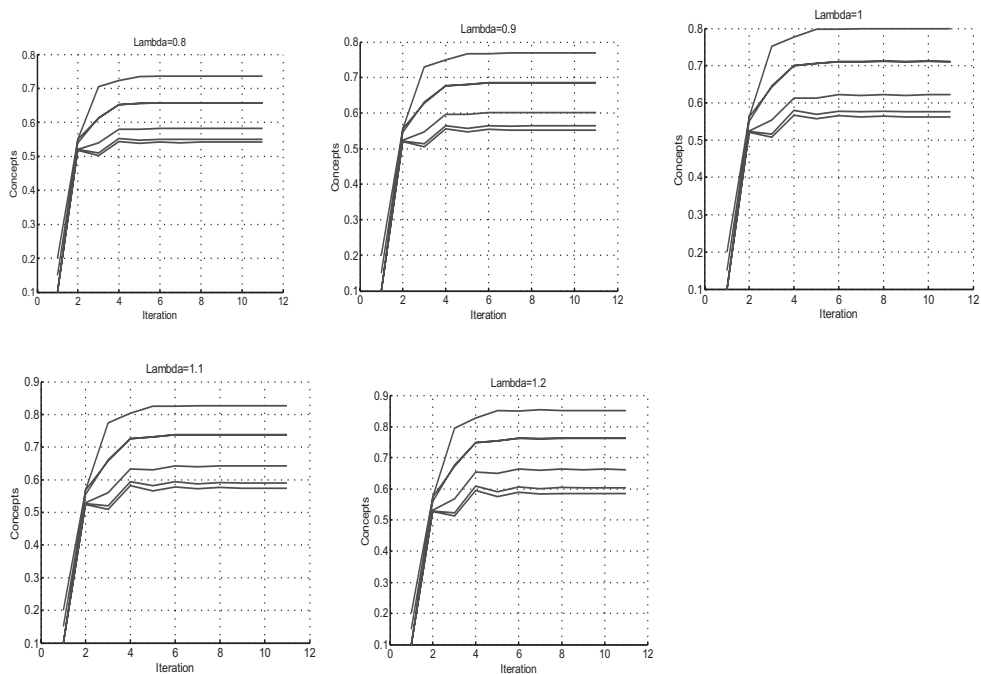

Fig. 1. The model simulation with λ = 0.8; 0.9; 1; 1.1 and 1.2

It may be observed that in the FCM model, all factors converged rather fast to a steady state. After the first five iterations, the transient behaviour seems to end and the FCM approaches an obviously stable state where each concept assumes a constant value ('plateau', depending on λ, between 0.5 and 0.9). While the qualitative behaviour of the simulation result is virtually independent of the steepness, the actual constant values to which the concept influence state converges are more or less similar, thus after normalization, the results are very consistent.

The initial states of the factors are known from Table 2. The final states of the concepts computed for each λ are shown in Table 4.

However, our strong assumption is that the time series is the most influencing input data in the modeling, to confirm this assumption we will also check in which way different expert matrices influence the results in the next phase of the research.

The final state of the concepts computed for each λ

	λ				
	0.8	0.9	1	1.1	1.2
C1	0.736	0.768	0.799	0.827	0.853
C2	0.659	0.685	0.711	0.737	0.762
C3	0.583	0.602	0.621	0.641	0.662
C4	0.541	0.552	0.563	0.574	0.585
C5	0.659	0.685	0.711	0.737	0.762
C6	0.551	0.563	0.577	0.590	0.603

The average results of simulation with different λ values are presented in the last column of Table 3. As integrated waste management systems are sophisticated and complex systems, priorities and targets need to be set up at the early stage of planning and implementation. Assuming, that the initial values are estimated more or less correctly by the experts, we might conclude the following main statement of the paper: the ranking of the factors below influencing the sustainability of the waste management systems shows the way how the roles and weights of the factors should be considered within an IWMS in order to ensure environmental efficiency, economical affordability and social acceptability, this way providing a comprehensive interdisciplinary framework for addressing all problems of managing urban solid waste.

1. C1 (technical factor),
2. C2 (environmental factor) and C5 (legal factor),
3. C3 (economic factor),
4. C6 (institutional factor),
5. C4 (social factor).

On the basis of this investigation, the priority sequence of factors or components in the waste management systems at the regional level might be declared.

According to the simulation, the first or most important issue is what materials are managed, treated and disposed of and how (features of the collection, transfer and treatment systems, e.g. material recovery, organic material treatment, thermal treatment, and final disposal). Then, the environmental and legal factors, economic issues of the system are following. Finally, the list closes with the social factor where the main issue is to accept the IWMS and to participate in its activities. However, the public plays an important role in sustainable waste management for which the awareness of waste reduction, segregation and recycling need to be enhanced.

We set up the FCM model of the IWMS, and implemented its structure in a way that its parameters and weights were flexibly variable. Even though the FCM model was proposed for the integrated analysis of the sustainability factors of the IWMS on a regional level, the validity of the method is depending on the reliability of the input data. As they were obtained from a wide scope of experts, we are convinced that by using the proposed new approach, sustainable waste management systems may be directly planned and established, at least in any more or less closed geographical area.

4.2. The Identification of the Elements of the Connection Matrix Using BEA

In our second experiment [36], 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 2010s. 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 [3–8] is based on a consensus concerning the interrelationship of the concepts playing a determinative role 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 therefore, it makes it unnecessary to continuously consult the experts in order to obtain up-to-date but entirely subjective data again and again.

Nevertheless, in order to speed up the learning procedure, and to some extent, out of scientific curiosity, we used the data collected from the above mentioned survey. It must be stressed that the results of these questionnaires (which were compared, and the medium values selected for each matrix element as the 'typical subjective values' 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. It turned out during the optimization, that the convergence speed is quite high with randomly generated start population as well, thus, prudent composition of the bacteria in the first generation was not an important issue. 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 (Table 1), including identification of concept nodes and their mutual relationships represented by the graph edges.

Simulation in this context consisted of computing the states of the system described by the state vector over a number of successive iterations. In every iteration cycle, the state vector specifies the current values of all factors (the nodes) in a particular moment. The values of the given states (nodes) are obtained from the preceding iteration values of all the nodes which exert influence on the given node through cause-effect relationship. The transformation function is used to confine the weighted sum to the range set to [0, 1]. This normalization hinders the absolute quantitative analysis, but allows the 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), see [37].

During the optimisation of our FCM with BEA, forced mutation [38] was used to increase the otherwise very low value of genetic diversity, to speed up computations in this manner. Forced mutation is a simple and easily implementable operator that slightly modifies some bacteria in the population if they seem very similar (typically in the final generations of the optimization). Forced mutation was applied in all subsequent generations after gene transfer.

The value of λ used by the transformation function was represented by the first gene of the bacteria. The following 30 genes corresponded to the elements of the 6×6 connection matrix (without the elements of the main diagonal, which were not stored).

The FCM determined the values of the factors in the subsequent iterations using the connection matrix. The goal of using the BEA heuristics was to find a connection matrix that minimizes the difference between the state values obtained from the literature (see Table 2) and the generated values of the factors. This difference d is expressed in Equation 3.

$$d = \sum_{t=1}^{6} \left(\left[c_i \right]_t - \left[\hat{c}_i \right]_t \right)^2 \tag{3}$$

where $[c_i]_t$ denotes the real and $[\hat{c}_i]_t$ the calculated values of factors.

The results of the optimization are contained in the connection matrix presented in Table 5. Here $\lambda = 1$, which resulted in $d = 0.727$ between the obtained and the state vectors suggested by experts. 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 elements, especially as it resulted from data obtained throughout a relatively long observation period. The fact that expert opinions differ so much from the objective reality definitely poses a question of how deep the insight of waste management experts may be wherever the system on hand is constituted from a set of complex technical, environmental and social subsystems consisting of several mutually influencing (and rather fluctuating) factors.

Table 5

The resulting optimized connection matrix

	C1	C2	C3	C4	C5	C6
C1	0	−0.393	1	−1	1	0.753
C2	0.212	0	1	−1	1	−1
C3	−0.722	1	0	−1	1	−1
C4	−1	0.377	−1	0	1	−1
C5	1	1	0.749	−1	0	−1
C6	−1	0.821	−1	−1	1	0

While in this approach we tried 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 [11], we found that results obtained with various, non-optimal steepness values λ, the results differed essentially only in the scaling. After normalization, all estimated time series predictions converged to essentially the same limit values.

5. Present research

From the unexpected results, the fact that the connection matrix obtained from the observation data is so thoroughly different from the matrix given by the experts that the obvious question arives of whether the approach and the objective results are mathematically stable enough in terms of the uncertainty of the observed values. It is also evident, that the program performed the simulation with different levels of credibility. In cases where input data correspond to reality, the method is suitable for simulating the problem and providing accurate results.

Based on the above results, in this paper, we propose the application of the systems of systems (SoS) approach to regional IWMS.

A system is the collection of main factors and their interrelationships gathered together to form a whole greater than the sum of its parts [41]. The knowledge necessary for managing complex projects, for the development complicated of systems, has not kept pace with the increasing complexity and integration of these projects themselves. This increased complexity has permitted some to establish distinctions among systems projects and to propose a framework of systems called the system of systems (SoS) [42].

Despite the fact that a waste management system consists of only six main factors, it is obvious now that properly overviewing the whole procedure needs an approach based on the systems of systems concept [36]. The latter approach is namely suitable to handle problems with essentially different types of system components' where interoperability and seamless interfacing is necessary. The application of this approach then easily leads to the unexpected emerging phenomena – such as the surprising values in the resulting connection matrix. The results obtained by the FCM model are unambiguously such emerging features that will necessarily lead to the re-evaluation of the knowledge and views of environmental engineers dealing with waste management.

From the unexpected results, 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 arives of whether the approach and the objective results are mathematically stable enough in terms of the uncertainty of the observed values. It is also evident, that the program performed the simulation with different levels of credibility. In cases where the input data correspond to reality, the method is suitable for simulating the problem and providing accurate results.

Based on the above results and conclusion, we propose the application of the systems of systems (SoS) theory.

The challenge with the SoS emerges in the interoperability and interfacing of the component systems. SoS integration is a method to pursue development, integration, interoperability, and optimization of systems to enhance performance, but it definitely needs a view that includes all views of the disciplines associated with the constituent systems.

We intended to resolve the contradictions between the previous models generated from observed time series on one side, and experts' estimated influence degrees on the other side, and to go below the level of generally recognized components, decomposing the factors into up to around fifty subcomponents, partly revealing interconnections among the main factors on a primary level. In order to be able to establish this extremely complex and completely novel model of IWMS, we applied the SoS approach which is shown in Fig. 2.
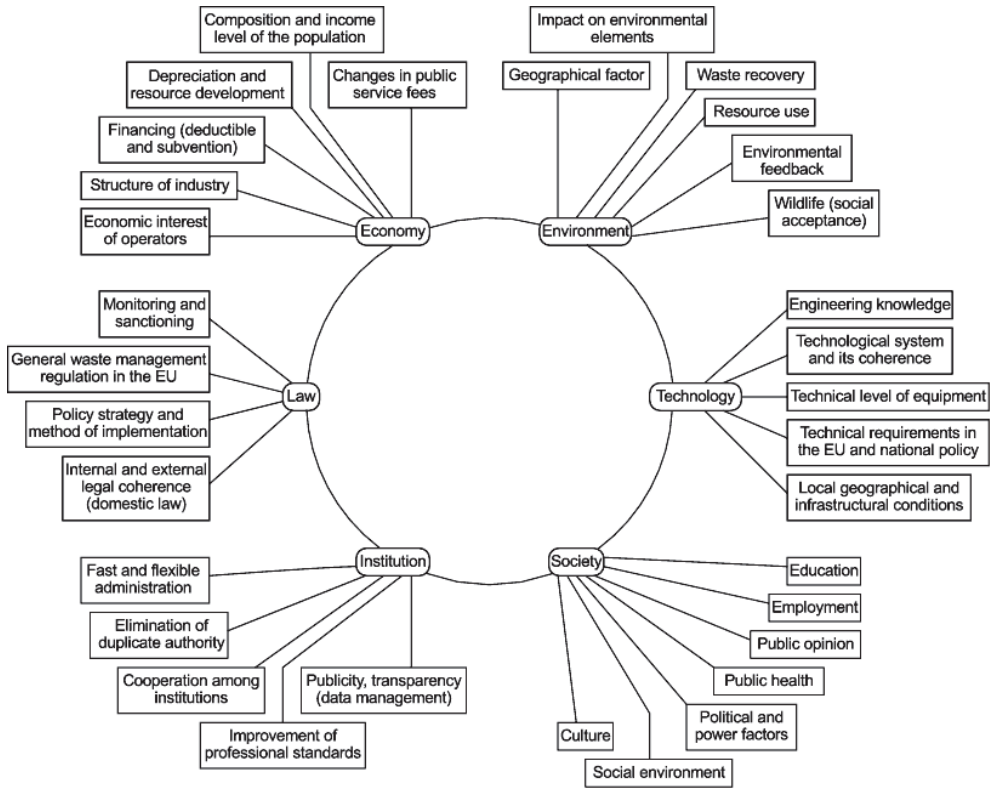
Fig. 2. Basic SoS approach: main factors and subcomponents of regional IWMS

This guaranteed that among subsystems of different types and with various influence surfaces complete interoperability and seamless interfacing could be provided, and thus a deeply justifiable and relevant hierarchical adaptive FCM network model of IWMS can be established that may be used for actually determining the optimal inputs belonging to any intended change in the sustainable states while adequately predicting any unexpected emerging phenomena as well.

In the close future, our intention is to also validate the developed model by experts with the help of the Delphi method and SWOT analysis. The expected results of the future investigation may help to determine the essential steps towards solving this complex problem in the long term and obtain technologies for the sustainable maintenance of the municipal waste management system.

6. Summary

The sustainable decision-making model is a combination of FCM and BEA soft computing tools. The proposed model provides an effective means of assisting in determining the

main effecting elements of IWMS in the decision-making process and to solve real world waste management problems. The model can quantify and qualify the degree of efficiency of the factors. The sustainable decision making model not only accommodates economic, environmental and social factors simultaneously, but also incorporates legal, institutional and technical issues.

In the future, we intend to carry out a sensitivity analysis of the above methods. In cases where 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 also be investigated by hybrid and combined evolutionary and memetic algorithms which were proven to be better than other simple algorithms.

In the recent past, some emerging economies have gone through a very rapid industrial development which resulted in an increase of their GDP. Because of the sharp rise in the production volume, it is very important to alleviate societal, economic and environmental concerns over the increased rate of resource consumption and waste production [43]. We also wish to extend our research to the investigation of the waste management of emerging countries.

R e f e r e n c e s

[1] Demirbas A., *Waste management, waste resource facilities and waste conversion processes*, Energy Conservation and management, 52, 2011, 1280-1287.

[2] Salhofer S., Wassermann G., Binner E., *Strategic environmental assessment as an approach to assess waste management systems. Experiences from an Austrian case study*, Environmental Modelling & Software, 22, 2007, 610-618.

[3] van de Klundert A., Anschutz J., *Integrated sustainable waste management: the selection of appropriate technologies and the design of sustainable systems is not (only) a technological issue*, Paper prepared for the CEDARE/IETC Inter-regional Workshop on Technologies for Sustainable Waste Management, 13–15 July 1999 Alexandria.

[4] Morrissey A.J., Browne J., *Waste management models and their application to sustainable waste management*, Waste Management, 24, 2004, 297-308

[5] Wilson E.J., McDougall F.R., Willmore J., *Euro-Trash: Searching Europe for a More Sustainable Approach to Waste management*, Resources Conservation and Recycling, 31, 2001, 327-346.

[6] Langa D.J., Binder C.R. et al., *Material and Money Flows as a Means for Industry Analysis of Recycling Schemes. A Case Study of Regional Bio-Waste Management*, Resources, Conservation and Recycling, 49, 2006, 159-190.

[7] den Boer J., den Boer E., Jager J., *LCA-IWM: A Decision Support Tool for Sustainability Assessment of Waste Management Systems*, Waste Management, 27, 2007, 1032-1045.

[8] Thorneloe S.A., Weitz K., Barlaz M., Ham R.K., *Tools for Determining Sustainable Waste Management Through Application of Life-Cycle Assessment: Update on U.S.*

Research, Seventh International Waste Management and Landfill Symposium V, 1999, 629-636.

[9] Kosko B., *Fuzzy cognitive maps*, Int. J. Man-Machine Studies, 24, 1986, 65-75.

[10] Perusich K., *System Diagnosis Using Fuzzy Cognitive Maps*, Cognitive Maps, Karl Perusich (Ed.), InTech, 2010.

[11] Buruzs A., Pozna R.C., Kóczy L.T., *Developing Fuzzy Cognitive Maps for Modeling Regional Waste Management Systems*, Civil-Comp Press, Proceedings of the Third International Conference on Soft Computing Technology in Civil, Structural and Environmental Engineering Computing, Y. Tsompanakis, (Ed.), Civil-Comp Press, Stirlingshire, Scotland 2013.

[12] Buruzs A., Hatwágner M. F., Pozna R.C., Kóczy L.T., *Advanced learning of fuzzy cognitive maps of waste management by bacterial algorithm*, IFSA World Congress and NAFIPS Annual Meeting (IFSA/NAFIPS), Joint. IEEE, 2013.

[13] Hung M., Ma H., Yang W., *A novel sustainable decision making model for municipal solid waste management*, Waste Management, 27, 2007, 209-219.

[14] Papageorgiou E., Kontogianni A., *Using Fuzzy Cognitive Mapping in Environmental Decision Making and Management: A Methodological Primer and an Application*, International Perspectives on Global Environmental Change, S. Young (Ed.), InTech, 2012.

[15] Özesmi U., Özesmi S.L., *Ecological models based on people's knowledge: a multi-step fuzzy cognitive mapping approach*, Ecological Modelling, Vol. 176, Issues 1–2, 15, 2004, 43-64.

[16] Stylos C.D., Georgopoulos V.C., Groumpos P.P., *The use of Fuzzy cognitive maps in modeling systems*, Proceedings of 5th IEEE Mediterranean Conference on Control and Systems, Paphos, Cyprus, July 21–23 1997.

[17] Stylos C.D., Georgopoulos V.C., Groumpos P.P., *The Use of Fuzzy Cognitive Maps in Modeling Systems*, Proc. of 5th IEEE Mediterranean Conference on Control and Systems, Paphos 1997.

[18] Balázs K. Kóczy L.T., Botzheim J., *Comparative Investigation of Various Evolutionary and Memetic Algorithms*, Computational Intelligence in Engineering, Studies in Computational Intelligence 313, I.J. Rudas, J. Fodor, J. Kacprzyk (eds.), Springer 2010, 129-140.

[19] Balázs K., Botzheim J., Kóczy L.T., *Comparison of Various Evolutionary and Memetic Algorithms*, Proc. of the International Symposium on Integrated Uncertainty Management and Applications, IUM 2010, Ishikawa 2010, 431-442.

[20] Dányádi Z., Balázs K., Kóczy L.T., *A Comparative Study of Various Evolutionary Algorithms and Their Combinations for Optimizing Fuzzy Rule-based Inference Systems*, Scientific Bulletin of 'Politechnica' University of Timisoara, Romania, Transactions on Automatic Control and Computer Science, Vol. 55, No. 69, 2010, 247-254.

[21] Balázs K., Kóczy L.T., *Constructing Dense, Sparse and Hierarchical Fuzzy Systems by Applying Evolutionary Optimization Techniques*, Applied and Computational Mathematics, Vol. 11, No. 1, 2012, 81-101.

[22] Balázs K., Horváth Z., Kóczy L.T., *Different Chromosome Based Evolutionary Approaches for the Permutation Flow Shop Problem*, Acta Polytechnica Hungarica, Vol. 2, No. 2, 2012, 115-138.

[23] Nawa N.E., Furuhashi T., *Fuzzy System Parameters Discovery by Bacterial Evolutionary Algorithm*, IEEE Transactions on Fuzzy Systems, Vol. 7, No. 5, 1999, 608-616.

[24] Nawa N.E., Furuhashi T., *A Study on the Effect of Transfer of Genes for the Bacterial Evolutionary Algorithm*, Second International Conference on Knowledge-Based Intelligent Electronic System, L.C. Jain, R.K. Jain (eds.), Adelaide 1998, 585-590.

[25] Nawa N.E., Hashiyama T., Furuhashi T., Uchikawa Y., *A Study on Fuzzy Rules Discovery Using Pseudo-Bacterial Genetic Algorithm with Adaptive Operator*, Proc. of IEEE International Conference on Evolutionary Computation, ICEC'97, 1997.

[26] Bäck T., Fogel D.B., Michalewicz Z., *Handbook of Evolutionary Computation*, IOP Publishing and Oxford University Press, 1997.

[27] Goldberg D.E., *Genetic Algorithms in Search, Optimization, and Machine Learning*, Addison-Wesley Publishing Company, Inc., 1989.

[28] Nawa N.E., Furuhashi T., *Fuzzy System Parameters Discovery by Bacterial Evolutionary Algorithm*, IEEE Transactions on Fuzzy Systems, Vol. 7, No. 5, 1999, 608-616.

[29] Pintér J.D., *Global Optimization in Action*, Kluwer Academic Publishers, Dordrecht 1996.

[30] Botzheim J., Cabrita C., Kóczy L.T., Ruano A.E., *Fuzzy Rule Extraction by Bacterial Memetic Algorithms*, International J. of Intelligent Systems, Vol. 24, 2009, 312-339.

[31] Gál L., Kóczy L.T., *Advanced Bacterial Memetic Algorithms*, Acta Technica Jaurinensis, Series Intelligentia Computatorica, Vol. 1, No. 3, 2008, 225-243.

[32] Botzheim J., Cabrita C., Kóczy L.T., Ruano A.E., *Fuzzy Rule Extraction by Bacterial Memetic Algorithm*, IFSA, Beijing 2005, 1563-1568.

[33] Gál L., Botzheim J., Kóczy L.T., *Modified Bacterial Memetic Algorithm used for Fuzzy Rule Base Extraction*, CSTST'08 Proc. of the 5th international conference on Soft computing as transdisciplinary science and technology, ACM, NY, USA, 2008, 425-431.

[34] Hatwágner F.M., Horvath A., *Parallel Gene Transfer Operations for the Bacterial Evolutionary Algorithm*, Acta Technica Jaurinensis, Vol. 4, No. 1, 2011, 89-112.

[35] Buruzs A., Pozna R.C., Kóczy L.T., *Developing Fuzzy Cognitive Maps for Modelling Regional Waste Management Systems*, Y. Tsompanakis, (ed.), Proc. of the Third International Conference on Soft Computing Technology in Civil, Structural and Environmental Engineering, Civil-Comp Press, Paper 19, Stirlingshire, UK, 2013.

[36] Buruzs A., Hatwágner M.F., Pozna R.C., Kóczy L.T., *Advanced Learning of Fuzzy Cognitive Maps of Waste Management by Bacterial Algorithm*, IFSA World Congress and NAFIPS Annual Meeting, IEEE, 2013, 890-895.

[37] Stach W., Kurgan L., Pedrycz W., Reformat M., *Genetic Learning of Fuzzy Cognitive Maps*, Fuzzy Sets and Systems, 153, 2005, 371-401.

[38] Hatwágner F.M., Horvath A., *Parallel Gene Transfer Operations for the Bacterial Evolutionary Algorithm*, Acta Technica Jaurinensis, Vol. 4, No. 1, 2011, 89-112.

[39] Hatwágner F.M., Horvath A., *Maintaining Genetic Diversity in Bacterial Evolutionary Algorithm*, Annales Univ. Sci. Budapest, Sec. Comp, Vol. 37, Budapest 2012, 175-194.

[40] Jamshidi M. (ed.), *Systems of System Engineering. Innovation for the 21th Century*, John Wiley & Sons, Inc. Hoboken, New Jersey, 2009, 480.

[41] Boardman J., Sauser B., *System of Systems – the meaning of of*, Proc. of the 2006 IEEE/SMC International Conference on System of Systems Engineering, Los Angeles 2006.

[42] Boardman J., Sauser B., *From prescience to emergence: taking hold of systems of systems management*, n.a.

[43] Al-Maaded M., Madi N.K., Kahraman R., Hodzic A., Ozerkan N.G., *An Overview of Solid Waste Management and Plastic Recycling in Qatar*, J. Polym Environ, 20, 2012, 186-194.

[44] Wilson E.J., McDougall F.R., Willmore J., *Euro-Trash: Searching Europe for a More Sustainable Approach to Waste management*, J. of Resources Conservation and Recycling, 31, 2001, 327-346.

[45] Shmeleva S.E., Powell J.R., *Ecological–economic Modelling for Strategic Regional Waste Management System*, J. of Ecological Economics, 59, 2006, 115-130.

[46] Hung, M.-L., Ma, H.-W., Yang W.-F., *A Novel Sustainable Decision Making Model for Municipal Solid Waste Management*, J. of Waste Management, Vol. 27, 2, 2007, 209-219.

[47] Salhofer S., Wassermann G., Binner E., *Strategic Environmental Assessment as an Approach to Assess Waste Management Systems. Experiences from an Austrian Case Study*, J. of Environmental Modelling & Software, Vol. 22, 5, 2007, 610-618.

[48] Carvalho J.P., *On the Semantics and the Use of Fuzzy Cognitive Maps in Social Sciences*, WCCI 2010 IEEE World Congress on Computational Intelligence, CCIB, Barcelona 2010.

[49] Ketipi M.K., Koulouriotis D.E., Karakasis E.G., Papakostas G.A., Tourassis V.D., *A Flexible Nonlinear Approach to Represent Cause–effect Relationships in FCMs*, J. of Applied Soft Computing, 12, 2012, 3757-3770.

[50] Kecman V., *Learning and Soft Computing, Support Vector machines, Neural Networks and Fuzzy, Logic Models*, The MIT Press, Cambridge 2001.

[51] Jang J.R., ANFIS, *Adaptive-network-based fuzzy inference system*, IEEE Trans. Syst., Man, Cybern., 23, 1993, 665-685.

[52] Frayman Y., Wang l.P., *Data mining using dynamically constructed recurrent fuzzy neural networks*, Research and Development in Knowledge Discovery and Data Mining, Vol. 1394, 1998, 122-131.