A Cognitive Map-Based Representation for Consumer Behaviour Modelling

Wladyslaw Homenda
Faculty of Economics and Informatics in Vilnius
University of Bialystok, Vilnius, Lithuania
Faculty of Mathematics and Information Science
Warsaw University of Technology, Warsaw, Poland
Email: homenda@mini.pw.edu.pl

Agnieszka Jastrzebska
Faculty of Mathematics and Information Science
Warsaw University of Technology, Warsaw, Poland
Systems Research Institute
Polish Academy of Sciences, Warsaw, Poland
Email: A.Jastrzebska@mini.pw.edu.pl

***Abstract*—Human behaviour modelling is a prominent example of an area in which information processing and understanding remains a challenge. Among crucial problems of this domain are heterogeneity, multiplicity and uncertainty of information. Behaviour modelling benefits from methods that enhance understanding of dependencies between phenomena and form a comprehensive model over a collection of elementary information granules. If we consider analytical application, quantitative predictive modelling becomes obsolete, because it is unable to represent wealth of information and its structuring. Hence, there is a need for semantic knowledge modelling. In light of the above, we present a Cognitive Map-based modelling framework capable to represent decision making processes. The model assumes that motivational stimuli determine decision making outcome. In case of human decision making, needs play the role of motivational stimuli. A decision is an outcome of processing of human needs. In order to reflect this using a Cognitive Map-based model, we assume that concepts making a map correspond to various needs. In the paper, we present a processing scenario that applies a Cognitive Map of needs and a current state of personal stimuli to produce a decision. We also apply the model to real-world data in an experiment of mobile phone activity monitoring.**

***Index Terms*—Cognitive Maps; Fuzzy Cognitive Maps; consumer behaviour modelling; decision making.**

I. INTRODUCTION

Human decision making elicits from an entangled collection of needs, and depends on the current state of mind and external conditions. Human decision making modelling is challenging both on the knowledge representation level and on processing level. First, human needs are not homogeneous, there are many of them, they are dependent one on another, and there is no objective and precise way to express their intensity and character. This is the case when applying a non-standard knowledge representation model that operates on abstract concepts. Particular implementation of a concept should be easy to interpret by a human being and it should relate to a corresponding need.

Even though needs are an internal collection of stimuli, they appear in some external context. In order to define a model reflecting the described assumptions, we require some variant of a semantic knowledge model with appropriate formalism for data processing.

We propose to apply Cognitive Maps to consumer decision making modelling. Cognitive Map is an example of a semantic knowledge model. It is a soft computing method composed of a collection of concepts and relationships between them. Processing with a Cognitive Map could be envisioned as follows: as the input, we provide data corresponding to a current state of phenomena. Map processes the input using concepts and dependencies between concepts and produces output data corresponding to the updated state of phenomena.

The key novelty introduced in this paper is the application of Cognitive Maps to consumer preferences and decision making modelling. So far, Cognitive Maps have been applied to: time series prediction on a linguistic level [1], pattern recognition [2] and system modelling and control [3].

The paper is structured as follows. Section II is a brief presentation of background knowledge on consumer decision making modelling. Section III introduces the new approach. Section IV addresses the method with the help of case studies. Section V concludes the paper.

II. LITERATURE REVIEW

In this section, we present a general overview of the most relevant streams of studies on consumer decision making modelling.

First, we need to mention the existence of a vast number of works on multi-criteria decision making. In this line of research, we come across methods for weighting and aggregating criteria relevant for a given decision. For instance, [4] addresses a multi-criteria decision making model utilising linguistic operators, while [5] addresses a method based on prioritised weighted aggregation with OWA (ordered weighted averaging) operator and t-norms. There is a wide range of papers in this domain employing various operators for aggregation and various models for knowledge representation. Among studies similar ours, we find methods that, apart from the task of criteria aggregation, take into account interactions between criteria. This, typically, is realised by assigning weights not only for individual criteria, but also to all combinations of criteria. Aggregation is performed for such extended formalism. An example of this approach based on Choquet integral playing the role of an aggregation function is presented in [6].

Another relevant group of studies revolves around preference modelling. Preference modelling is focused on comparing available alternatives. Let us assume we have objects x and

 ISBN: 978-1-61208-600-2

y from set X. We denote that x is at least as good as y as: $x \succsim y \Leftrightarrow f(x) \geqslant f(y)$, where $f : X \to \mathbb{R}$ is a valuation function that measures how good a given alternative is. In addition, in many applications a strict preference relation, denoted as $\succ$, is used. Apart from predominantly theoretical studies on preference relations, like [7], the literature offers impressive machine learning methods for preference learning. Their aim is to use training data to form a model that automatically performs alternatives' ranking. Here, we find SVM$^{\text{rank}}$ which solves an optimisation problem aiming at alternatives ranking [8], the ListNet [9] which is an algorithm based on neural network and gradient descent.

A Cognitive Map is a soft computing method forming a semantic knowledge model over a set of concepts. A map is a weighted digraph: it consists of concepts (vertices) and directed weighted edges linking the concepts. The philosophy of modelling with Cognitive Maps is very simple: concepts correspond to phenomena, linkages to relationships between phenomena. Weights inform about character and strength of connection. Weights are collected in a weight matrix. Such minimal formalisation encouraged extensive research on Cognitive Maps and led to the development of related sub-families, i.e., Fuzzy Cognitive Maps, Granular Cognitive Maps, etc. Versatility of the original formalism of Cognitive Maps proved to be so desirable and successful, that it has remained unchanged in all named sub-kinds of Cognitive Maps. What differentiates them is the assumed information representation model: crisp in Cognitive Maps, fuzzy in Fuzzy Cognitive Maps, granular in Granular Cognitive Maps, etc.

Intensive research on Cognitive Maps in application to knowledge processing started with a ground-breaking paper by B. Kosko [10]. The referenced paper presents a generalisation of Cognitive Maps to Fuzzy Cognitive Maps. More importantly, it presents a simple method for weight matrix learning. Nowadays, major studies on Cognitive Maps revolve around Fuzzy Cognitive Maps trained using a bio-inspired metaheuristic optimisation algorithm of choice. As mentioned, experimental fields, where Fuzzy Cognitive Maps have been successfully utilised include systems modelling and control, time series analysis, and pattern recognition.

In this paper, we present an application of Cognitive Maps to human decision making modelling, which is a novel and original contribution.

III. Preliminaries

A. Consumer Representation

The primary task is to define a model for consumer representation that will be the backbone of decision making modelling framework. Inspired by the research of K. Lewin on psychophysical field [11], we assume that a vector of all needs represents each consumer. Such infinite vector is a subject for further modelling. The vector in its most general form is given as:

$$\mathbf{x} = [x_1, x_2, \ldots]^T \tag{1}$$

$\mathbf{x}$ represents a given consumer, $x_i, i = 1, 2, \ldots, +\infty$ stands for his i-th need. It is worth to explain that a vector of needs $\mathbf{x}$ is of finite length in any practical application. Infinity in its description underlines that, despite its finiteness, we do not put restriction on its length, see below for details.

Each need in the vector is evaluated using a selected information representation scheme. In order to choose a particular model, one shall consider properties that are the most desired in a given application area. In our experiments, we considered crisp information and fuzzy sets [12], but there are other options available, for instance intuitionistic fuzzy sets.

In theory, the needs vector is infinite, because the set of needs is infinite. One aspect of human development is that it is accompanied by recognition of new needs. This phenomenon is explained by Maslow, [13], who states that after satisfying needs of a prime urgency, humans naturally start recognising more refined desires. Moreover, identification of new needs could be triggered by external stimuli, especially skilful marketing communication. The framework presented in this paper operates on a finite set of needs. This limitation is necessary, not only for computational reasons, but also because it is the only sensible convention to focus on needs relevant to a problem of interest. In practice, relevant needs must be identified before empirical data is collected. Let us give a few examples of sets of needs relevant in different decision making problems:

- needs relevant when we consider a particular car purchase: number of seats, capacity for carrying goods, ease of access to repair shops, level of extravagance associated with the car, etc.
- needs relevant when shopping for cleaning supplies: wood cleaner, glass cleaner, disinfectant, etc.
- needs related to an evening outing: concert, restaurant, theatre, visiting friends, etc.

Most importantly, the model allows describing causality. A particular needs vector describes preferences at a given at a given moment in time. Building consecutive vectors, with different needs evaluations will allow to represent time flow and illustrate change of needs.

The strength of motivational stimuli is expressed through needs evaluation. The method of evaluation depends on selected information representation model. If we employ classical set theory, a need either exists or it does not. Hence, evaluation of a need relies on selecting a number from the set $\{0, 1\}$. In contrast, with fuzzy set theory, needs are evaluated as real numbers from the interval $[0, 1]$. We can also perform needs evaluation based on linguistic variables or some other method we find suitable.

The model is capable to describe and discover dependencies at various levels of generality. This derives from the fact that we can easily group specific needs into more general clusters or the other way around: based on a general group of needs, we can transition into a fine-grained analysis, depending on the availability of data. For example, a general type of need

 ISBN: 978-1-61208-600-2

for existence includes all needs for food. The need for food contains a need for carbohydrates. The need for carbohydrates may be satisfied by consuming rice, bread, pasta, cookies, and so on. The structure is recursively nested.

Additionally, this relatively simple form of consumer representation allows sophisticated analysis, if we consider an abstract space of consumers described by their needs. In such a space, we may define classes of consumers and detect similarity between classes of consumers.

B. Processing with Cognitive Maps and Fuzzy Cognitive Maps

A Cognitive Map is a graph-based knowledge representation model. Let us denote the vertices in the map as $A_1, A_2, \ldots, A_c$, where c represents the number of vertices. Vertices correspond to abstract concepts. The strength of relationships between the vertices is denoted using weights: w_{11}, $w_{12}, \ldots w_{cc}$, where w_{ij} is a weight going from the concept A_i to the concept A_j. Weights are gathered in a $c \times c$ weight matrix denoted as $\mathbf{W}$. Particular values assumed by w_{ij} depend on an assumed information representation system (fuzzy, crisp, etc.).

In (regular) Cognitive Maps, weights assume values from the set $\{-1, 0, 1\}$. -1 indicates that an increase in a source node is correlated with a decrease in a destination node. 0 denotes lack of relationship. 1 informs that an increase in a source node causes increase in a destination node.

The constricted set of values allowed in regular Cognitive Maps limits their flexibility. The formulation of Fuzzy Cognitive Maps appeared as a remedy for this issue. In Fuzzy Cognitive Maps, relationships are expressed using real numbers from the $[-1, 1]$ interval [10].

Processing with any Cognitive Map is realised in the following way: as the input to the map we pass c activations gartered in a c-dimensional vector, where one activation is for one node in the map. Let us denote the vector of activations as $\mathbf{x} = [x_1, \ldots, x_c]^T$. Activations are the input data and they correspond to the state of nodes (the state of excitement of needs) at the current moment in time tm. The map processes the input using weights $\mathbf{W}$ and, as a result, we obtain the output. Let us denote the output as $\mathbf{y} = [y_1, \ldots, y_c]^T$. The output is interpreted as the state of nodes in the next moment in time $(tm + 1)$. In other words, the Cognitive Map models changes of a system of concepts in time. The idea behind processing with a Cognitive Map composed of three nodes is illustrated in Figure 1. Computations are formally represented as follows:

$$\mathbf{y} = \mathbf{W} \star \mathbf{x} \tag{2}$$

where $\star$ is an operation on a matrix and a vector.

Typically, but not always, in Cognitive Maps, input and output vectors are evaluated using values from the set $\{0, 1\}$, while Fuzzy Cognitive Maps use real numbers from the interval $[0, 1]$. Particular examples of implementations of $\star$ operation are given in Section IV.

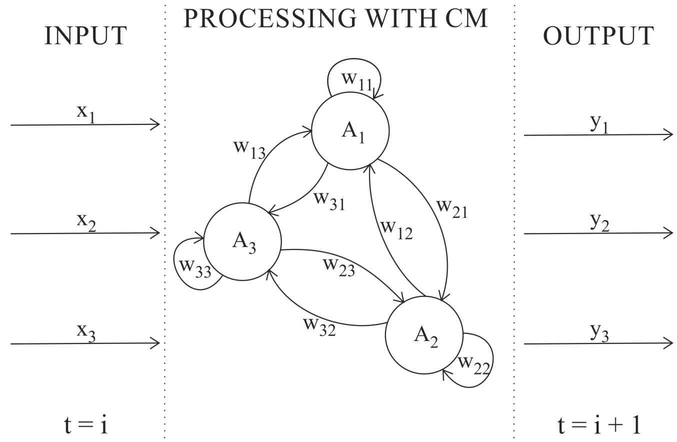

Fig. 1. Processing with a Cognitive Map (CM) with three nodes.

Map outputs represent state of nodes in the next moment in time. We wish that the predicted states are as close as possible to the actual states observable in future. In other words, maps allow predicting. The prediction quality is expressed by calculating similarity between map output $\mathbf{y}$ and desired target values, denoted as $\mathbf{t}$. This could be expressed as:

$$\mathbf{y} \sim \mathbf{t} \tag{3}$$

$\mathbf{t} = [t_1, t_2, \ldots, t_c]^T$ is the desired, ideal target.

The modelling outcome depends on the weight matrix. There are three strategies that could be executed in order to obtain a weight matrix:

- involve human experts to manually propose a weight matrix,
- run supervised learning procedure to extract a weight matrix automatically from data,
- hybrid learning: use expert knowledge to define fine-grained conditions to facilitate a better performance of a learning algorithm.

The first approach is the most inconvenient, because in order to build a map, we need human involvement and the procedure is manual. The substantial advantage of this approach is that when a Cognitive Map is constructed by experts, its formalism is well understood. Humans provide a structured representation of phenomena in a way that is easy to interpret and conveys a meaningful description.

Automated weight matrix learning has the big advantage that it does not require the considerable effort needed when we involve human experts. In this case, we use historical data to obtain a weight matrix. In practice, there are a few obstacles in this approach. First, not all applications have enough historical data. Second, trends in development of algorithms have brought forward nature-inspired optimisation heuristics, like Genetic Algorithm, Particle Swarm Optimisation, and so on. They are applied in areas when optimisation is difficult, as this one, and their motto is (so to speak) “close enough is good enough”. More formally speaking, they do not guarantee convergence to the optimum. In many domains

 ISBN: 978-1-61208-600-2

of applied Cognitive Maps, for instance in classification, this property does not affect the modelling outcome as weights of connections between map nodes do not matter as much as the outcome, which is, an assigned class label. In contrast, if we want to obtain a meaningful knowledge about relationships between the nodes, the "close enough is good enough" motto is not what we shall be content with. It might happen that two, substantially different maps (meaning: maps with drastically different evaluations of weights) could provide similar numerical modelling accuracy.

C. Cognitive Map-based Consumer Needs Representation

In our approach to human decision making modelling, we assume that needs determine actions. We apply the field theory of K. Lewin, who is recognised as the founder of social psychology, [14]. The field theory can be transparently transformed into a mathematical model. This is a rare and valuable property, because many psychological theories are rather descriptive than quantitative. The field theory says that at a given moment in time we exist within or, to put it in another words, we own a certain abstract psychophysical field comprising of all needs there are. The strengths of needs in a psychophysical field change over time. The reason for change could be internal or external. There is also an assumption that any part of a psychophysical field depends on its every other part. Human behaviour can be explained by analysing forces acting in the field.

Our model captures the moment when needs get re-evaluated in response to new input conditions. Hence, we assume that:

- a Cognitive Map represents relationships between human needs,
- input data (activations) of the Cognitive Map correspond to the current strength of motivational stimuli,
- the Cognitive Map's output represents strength of needs in response to the input, analysing the output allows to make a decision.

The premise behind introducing Cognitive Maps to represent consumer needs was dictated by review of the literature on needs taxonomies. We see an insufficient focus on methods that take into account relationships between the needs.

In future, we plan to impose certain conditions on the needs model. In this case, the most advanced, and at the same time interpretable, form of an arbitrarily defined set of conditions is an ontology of needs.

IV. CASE STUDY

In this section, let us introduce a few examples of application of Cognitive Maps to consumer decision making and preference modelling.

Two case studies are arbitrarily defined. They concern decision making modelling using a regular Cognitive Map and a Fuzzy Cognitive Map. The discussion is limited to relatively small maps representing five needs:

- listening to a radio,
- watching a TV,
- reading a book,
- playing with a dog,
- taking a walk.

The third case study presents another application of the model - to consumer space modelling. We apply a Fuzzy Cognitive Map to process a dataset describing mobile network activity.

A. Cognitive Map for Decision-Making Modelling

The first example covers the most basic version of the model. Is is based on a (regular) Cognitive Map, in which relationships between the nodes are expressed as values from the set $\{-1, 0, 1\}$. Input activations assume values from the set $\{0, 1\}$. We analyse a Cognitive Map for one consumer. Relationships between needs were defined arbitrarily and are displayed in Figure 2.

Activations describe current excitement levels of the needs under consideration. Let us assume, that the consumer reports the following activations: $\mathbf{x} = [0; 0; 1; 1; 0]^T$. The activations order corresponds to the list mentioned above. We interpret it as follows: lack of need for listening to a radio, watching a TV and taking a walk; existing need for reading a book and playing with a dog.

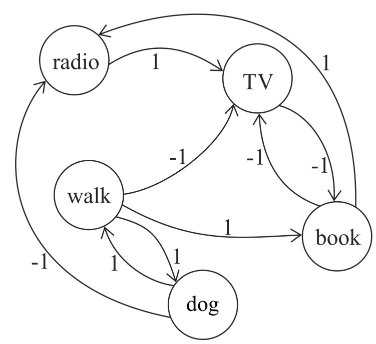

Fig. 2. Arbitrarily defined Cognitive Map for the case study consumer.

We propose to apply the following, very simple, scheme to implement the $\star$ operation, cf. (2). A single output y_i is calculated as follows:

$$y_i = \sum_{j=1}^{c} w_{ij} \cdot x_j \tag{4}$$

c denotes the number of nodes in the map. In this case, $c = 5$. For simplicity, we do not introduce any scaling to the outcome of the sum of products. Therefore, y_i assumes a value from the set $\{-c, -(c-1), \ldots, 0, \ldots, c-1, c\}$. The Maximum value in the output vector indicates a decision. It is very easy to imagine more sophisticated aggregation schemes.

Let us present the decision making modelling based on the stated assumptions:

$$\begin{array}{c} radio \\ TV \\ book \\ dog \\ walk \end{array} \begin{bmatrix} 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & -1 & 0 & 0 \\ 1 & -1 & 0 & 0 & 0 \\ -1 & 0 & 0 & 0 & 1 \\ 0 & -1 & 1 & 1 & 0 \end{bmatrix} \star \begin{bmatrix} 0 \\ 0 \\ 1 \\ 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ -1 \\ 0 \\ 0 \\ 2 \end{bmatrix}$$

In response to the presented activations, the need to go for a walk will be perceived as the strongest.

B. Fuzzy Cognitive Map for Decision Making Modelling

In the second case study, we present a Fuzzy Cognitive Map constructed for one consumer concerning the same set of five needs as in the previous example. The map was defined arbitrarily and is displayed in Figure 3.

Let us recall that in Fuzzy Cognitive Maps weights are evaluated as numbers from the $[-1, 1]$ interval, while activations and outputs are numbers from the $[0, 1]$ interval. The implementation of the $\star$ operator from (2) on the level of a single node is realised as follows:

$$y_i = f\big(\sum_{j=1}^{c} w_{ij} \cdot x_j\big) \tag{5}$$

for $i = 1, 2, \ldots, c$. f is a squashing function, which draws the product to the $[0, 1]$ interval. The sigmoid function with a steepness parameter $\tau > 0$ is most commonly used.

$$f(u) = \frac{1}{1 + e^{-\tau u}} \tag{6}$$

We assumed $\tau = 5$ based on literature [15].

Fuzzy Cognitive Maps allow greater flexibility in expressing preferences and relationships between needs.

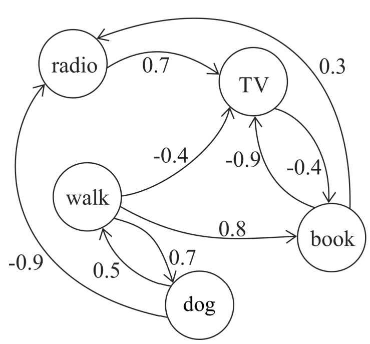

Fig. 3. Arbitrarily proposed Fuzzy Cognitive Map for the case study.

Let us assume, that current activations for the consumer, for whom we defined the Fuzzy Cognitive Map, are as follows: $\mathbf{x} = [0.1; 0; 0.4; 0.1; 0.6]^T$. The activations vector $\mathbf{x}$ informs us that out of five considered options (radio, TV, book, playing with a dog, and walking) the consumer has the strongest urge to go for a walk, watching TV is a non-existing stimulus, playing with a dog and listening to a radio are a couple of very weakly recognised needs, reading a book is a weakly moderate need. Let us present the computations in this case:

$$\begin{array}{c} radio \\ TV \\ book \\ dog \\ walk \end{array} \begin{bmatrix} 0 & 0.7 & 0 & 0 & 0 \\ 0 & 0 & -0.4 & 0 & 0 \\ 0.3 & -0.9 & 0 & 0 & 0 \\ -0.9 & 0 & 0 & 0 & 0.5 \\ 0 & -0.4 & 0.8 & 0.7 & 0 \end{bmatrix} \star \begin{bmatrix} 0.1 \\ 0 \\ 0.4 \\ 0.1 \\ 0.6 \end{bmatrix} = \begin{bmatrix} 0.5 \\ 0.3 \\ 0.5 \\ 0.7 \\ 0.9 \end{bmatrix}$$

The modelling outcome, $\mathbf{y} = [0.5; 0.3; 0.5; 0.7; 0.9]^T$, informs us that taking a walk is the most likely choice for this person. The need for walking is the strongest at the computed moment in time. The second strongest need in the output vector $\mathbf{y}$ is the need for playing with a dog computed as 0.7. A strong positive connection, that joins walking with playing with a dog, caused the strength of this need to increase from 0.1 to 0.7.

C. The Mobile Activity Dataset

Preferences analysis concerns not only heterogeneous, but also homogeneous markets. It is a common practice to perform segmentation of heterogeneous markets into homogeneous groups. Further analysis of consumer preferences within one, homogeneous segment is an important assignment. An example of a homogeneous good is mobile network service. Importantly, statistics collected by mobile network service providers contain significant valuable information about cities and their citizens. It has been proposed to use subscriber's location statistics to traffic monitoring in public transportation services, [16]. Public transportation services, alike mobile services, are homogeneous goods, especially when we consider large cities.

We propose to apply a Fuzzy Cognitive Map to model and predict potential demand for public transportation services based on mobile subscriber's location statistics. We process data collected as a part of the VaVeL project (VaVeL: Variety, Veracity, VaLue [17]), concerning traffic in mobile networks recorded by Base Transceiver Stations in Warsaw. The data was collected hourly, starting from 0:00 on 9th January 2017, ending at 23:00 on 20th January 2017. We scaled it to the interval $[0.1, 0.9]$ so that the training procedure for a Fuzzy Cognitive Map can be conducted without numerical problems.

The course of experiment was as follows. First, we arbitrarily selected data from four neighbouring zones, out of the total of 895 geographical zones in the city. For each zone, we have information (a time series) concerning the number of mobile network subscriber's registered at each hour. We assume the sliding window model with three time points within one window. Based on these assumptions, we form a Fuzzy Cognitive Map based on 12 concepts, four zones multiplied by three moments in time (length of sliding window) gives us 12. The first three concepts correspond to the first zone, the next three concepts correspond to the second zone, etc. We formed activations and targets to represent changes of concepts states in time (in other words, changes of traffic). Predictions are for one step ahead. The complete methodology of this approach was discussed in [18]. There are two alternative methods of how to use a sliding window Fuzzy Cognitive Map model. The first is that we average the model responses and produce a time series prediction in the form of a sequence of numbers. In this case a particular prediction is one point. The second method, more suitable for this study, is when we obtain a prediction in the form of a sequence of intervals. In this case a particular prediction is in the form of a lower and an upper interval limit, between which we assume that the state of phenomena is acceptable.

We run Particle Swarm Optimization to determine the best weights by minimization of Mean Squared Error between the Fuzzy Cognitive Map responses and target values:

$$MSE = \frac{1}{N \cdot c} \sum_{i=1}^{N} \sum_{j=1}^{c} (y_{ji} - t_{ji})^2 \qquad (7)$$

N is the number of samples, c is the number of nodes, y are map responses, t are targets. We used 160 pairs of activation and target for map training and the remaining 80 pairs were left for model testing. We can technically perceive the data used for map training as a time series of four variables.

In addition, in the application of traffic monitoring, it is worth to consider softening decision rules. In particular, we can extend the interval of acceptable values by some reasonable value. An example of a measure that can be used to evaluate the degree to which we expand margins is standard deviation.

In order to verify if we trained a correct model we plot predicted interval limits and actual values of time series for the four studied zones. This is presented in Figure 4 for train and test sets. We soften the decision margin by adding half of standard deviation for each variable. The four variables have the following standard deviations: 0.1742, 0.2526, 0.1111, 0.0523. The predicted lower (green) and upper (red) limits for the four zones are illustrated in Figure 4. Black lines present true levels of traffic. The MSE for the four studied zones is present in each plot. We can conclude that the model was properly trained.

After the Fuzzy Cognitive Map was trained and we verified that it correctly describes the given data, we use it as a decision making aid. The application of the Fuzzy Cognitive Map can be informally described as follows. A person is planning to travel through the four zones. He collected information about the traffic in the last three hours in these zones and passes it as the input to the map. The map calculates a pessimistic and an optimistic prediction for the next moment in time. The person can decide whether to go or not to go.

Since the above application is trivial, we additionally tested the model in two less standard scenarios:

- How does the Map react if the input is consistently distorted? Consistently distorted input corresponds to a continuous sequence of recorded and known anomalous states of phenomena.

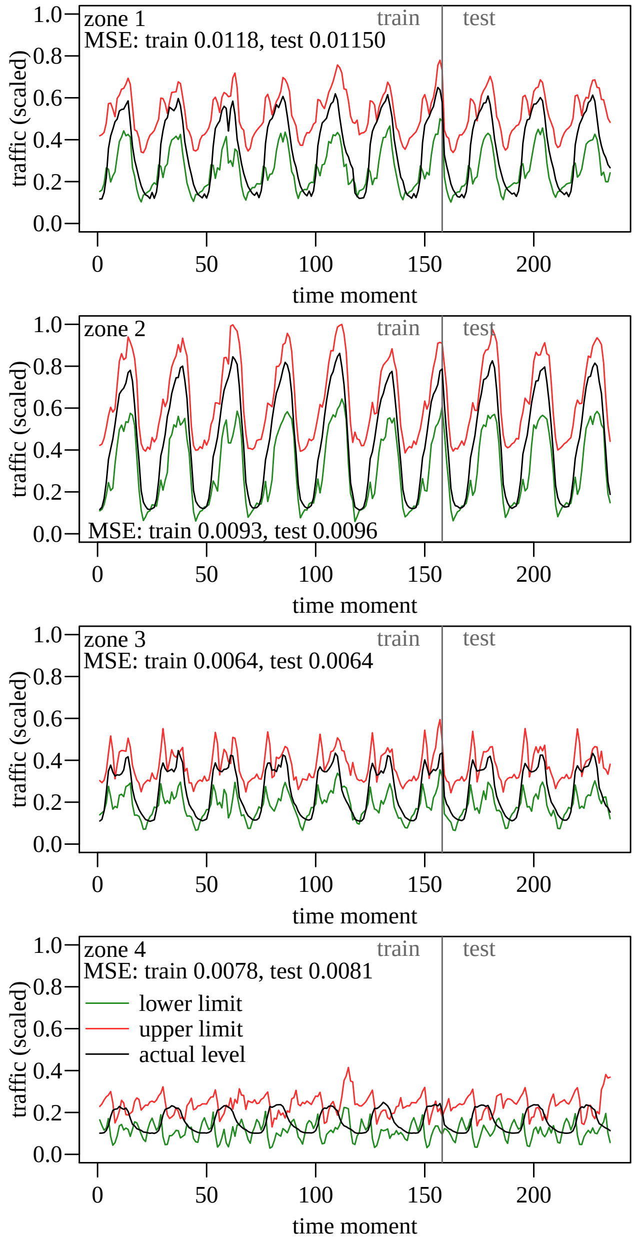

Fig. 4. Time series predictions for train and test sets in investigated zones.

- Is the Map sensitive to singular anomalies? Singular anomalies appear as single events, they are not preceded by anomalous events.

In Table I we present average coverage of train and test set observations by predicted intervals. The notion of coverage is quite straightforward, namely it is the number of true observations falling into predicted intervals. Intervals are spanned by the factor of a fraction of standard deviation. Without surprise, the more we expand the interval, the greater the coverage gets.

An analogous experiment was conducted for test data distorted with systematic noise. For this experiment, we added or subtracted a constant value to or from all activation vectors. We run activations with the Fuzzy Cognitive Map and we computed the average coverage of map outputs. The first test

TABLE I. AVERAGE COVERAGE OF TRAIN/TEST TIME SERIES DATA POINTS FOR PREDICTIONS WITHOUT AND WITH A SPANNING FACTOR

	interval spanning factor					
	zero		+0.2sd		+0.5sd	
zone	train	test	train	test	train	test
z1	0.3987	0.3506	0.5633	0.3506	0.7278	0.7403
z2	0.2848	0.2468	0.6392	0.2857	0.9304	0.8831
z3	0.4114	0.4026	0.5886	0.4805	0.7532	0.7532
z4	0.2215	0.2208	0.2721	0.2468	0.3734	0.3766

TABLE II. COVERAGE FOR TEST DATA MODIFIED WITH SYSTEMATIC DISTORTIONS

	interval spanning factor		
zone	zero	+0.2sd	+0.5sd
z1	0.1169	0.2468	0.3117
z2	0.2208	0.2987	0.3766
z3	0.1429	0.2078	0.3377
z4	0.1818	0.1948	0.2468

was performed for the original model, with the lower and the upper interval limits produced by the map. The next two tests were performed for intervals expanded by constant value equal to 0.2 of standard deviation and by 0.5 of standard deviation. The results are displayed in Table II. Without surprise, coverage is smaller, in comparison with results in Table I. Consistently, as we expand intervals, coverage grows.

Further experiments were for data that simulated unexpected anomalies. Anomalies were added randomly to target data. We can visually verify susceptibility of the trained Map to random distortions. The results (for a couple of zones) are illustrated in Figure 5. Random anomalies were generated by adding positive numbers drawn randomly from normal distribution with mean equal to 0 and standard deviation equal to 0.3. We added anomalies to 30 randomly selected values from the test set. Figure 5 concerns predictions expanded by 0.5 of standard deviation.

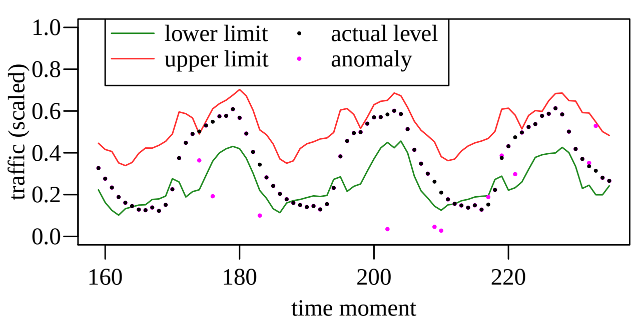

Fig. 5. Predictions for zone 1 test set with added anomalies.

V. CONCLUSION

In the paper, we have introduced a consumer decision making modelling approach based on Cognitive Maps and a vector-based representation of consumer needs. The method is flexible. Not only does it allow to model decision making processes, but also structures in consumer and needs spaces. The approach is on one hand easy to interpret, as a map provides a semantic knowledge representation, and, on the other hand, powerful, as the weight matrix can be automatically trained from historical data.

The intention of this paper was to introduce the idea of a versatile model for consumer preferences representation and modelling. The model requires further development and experimenting. We would like to emphasise that our study on homogeneous preferences analysis and the mobile activity dataset are in a very early stage. In future, we plan to analyse this dataset to a greater extent.

ACKNOWLEDGMENT

This research has been supported by the European Union's Horizon 2020 research and innovation programme under grant agreement No. 688380 *VaVeL: Variety, Veracity, VaLue: Handling the Multiplicity of Urban Sensors*.

REFERENCES

[1] W. Stach, L. Kurgan, and W. Pedrycz, "Numerical and linguistic prediction of time series with the use of fuzzy cognitive maps," vol. 16, pp. 61 – 72, 2008.

[2] G. A. Papakostas, Y. S. Boutalis, D. E. Koulouriotis, and B. G. Mertzios, "Fuzzy cognitive maps for pattern recognition applications," vol. 22, no. 8, pp. 1461 – 1486, 2008.

[3] P. P. Groumpos and C. D. Stylios, "Modelling supervisory control systems using fuzzy cognitive maps," *Chaos, Solitons & Fractals*, vol. 11, no. 1, pp. 329 – 336, 2000.

[4] M. Aggarwal, "Adaptive linguistic weighted aggregation operators for multi-criteria decision making," *Applied Soft Computing*, vol. 58, pp. 690 – 699, 2017.

[5] H.-B. Yan, V.-N. Huynh, Y. Nakamori, and T. Murai, "On prioritized weighted aggregation in multi-criteria decision making," *Expert Systems with Applications*, vol. 38, no. 1, pp. 812 – 823, 2011.

[6] V. Cancer, "Considering interactions among multiple criteria for the server selection," vol. 34, no. 1, pp. 55 – 65, 2010.

[7] M. Roubens and P. Vincke, *Preference Modeling*. LNEMS 250, Springer Verlag, Berlin, 1985.

[8] T. Joachims, "Training linear svms in linear time," in *Proceedings of the ACM Conference on Knowledge Discovery and Data Mining (KDD)*, 2006.

[9] Z. Cao, T. Qin, T.-Y. Liu, M.-F. Tsai, and H. Li, "Learning to rank: From pairwise approach to listwise approach," in *Proceedings of the 24th International Conference on Machine Learning*, 2007.

[10] B. Kosko, "Fuzzy cognitive maps," vol. 24, pp. 65 – 75, 1986.

[11] K. Lewin, *Field Theory in Social Science*, D. Cartwright, Ed. Harper & Brothers, 1951.

[12] L. A. Zadeh, "Fuzzy sets," vol. 8, no. 3, pp. 338 – 353, 1965.

[13] A. Maslow, "A theory of human motivation," vol. 50, no. 4, pp. 370 – 396, 1943.

[14] S. J. Haggbloom, J. E. Warnick, V. K. Jones, G. L. Yarbrough, T. M. Russell, C. M. Borecky, R. Mcgahhey, J. L. I. Powell, J. Beavers, and E. Monte, "The 100 most eminent psychologists of the 20th century," vol. 6, no. 2, pp. 139 – 152, 2002.

[15] W. Stach, L. Kurgan, and W. Pedrycz, "A survey of fuzzy cognitive map learning methods," pp. 71 – 84, 2005.

[16] M. Luckner, A. Roslan, I. Krzeminska, J. Legierski, and R. Kunicki, "Clustering of mobile subscriber's location statistics for travel demand zones diversity," in *LNCS*, K. Saeed, W. Homenda, and R. Chaki, Eds., vol. 10244, 2017, paper 315 – 326.

[17] Vavel: Variety, veracity, value: Handling the multiplicity of urban sensors. [Online]. Available: http://www.vavel-project.eu/

[18] A. Jastrzebska and W. Homenda, "Modeling time series with fuzzy cognitive maps," in *Proc. of the IEEE World Congress on Computational Intelligence*, 2014, pp. 2572 – 2579.