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NEURO-FUZZY MODELS AND TOBACCO CONTROL

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Abstract

The paper presents neuro-fuzzy models' application appropriate for tobacco control: the fuzzy control model, Adaptive Network Based Fuzzy Inference System, Evolving Fuzzy Neural Network models, and EVOlving POLicies. We propose further the use of Fuzzy Casual Networks to help tobacco control decision makers develop policies and measure their impact on social regulation.

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INTRODUCTION

Given that tobacco smoking is a largely preventable cause of death [11] the attempts to control tobacco usage have become part of the contemporary government policy in many countries [16]. Tobacco control social regulation has effects in pursuit of public policy of reduced incidence of smoking related ill-health and premature death. As such tobacco control plays an important role in minimising negative effects of tobacco use [5].

Governments, supported by medical evidence, antismoking social movements and interests groups, are increasing their activities on regulations concerning tobacco control. Development of any government policy, including smoking control policy, observed as a decision making process, is primarily supported by supplying data and information to decision makers. Decision support systems, of which neuro-fuzzy systems are one [7], are not often used in developing government regulations [8]. Very little academic research in this area using either fuzzy logic or neuro-fuzzy system support has been published. According to a literature review, fuzzy logic approach has been implemented in energy policy planning [9], security policies [10] and health policy [11]. It seems there is no, however, literature evidence of using neuro-fuzzy systems in government social policy regulations, apart of [1, 5, 12, 13]. Highly commended preliminary research undertaken used both fuzzy control and neuro-fuzzy modelling to identify the factors influencing the effectiveness of measures to prevent tobacco smoking. That work provides a solid basis for evaluating the effectiveness of the reformed social regulatory measures affecting tobacco smoking.

With this paper we want to emphasize that the decision support systems based on neuro-fuzzy models help to improve the tobacco control social regulation process to either quit or minimise negative effects caused by cigarettes smoking.

WHAT IS WELL-KNOWN

As a reasoning process, decision making leads to the selection of one course of action from among several considerations [18]. Governmental decisions' alternatives involve a large number of considerations. In the decision process they may not all be taken into consideration, with some of them being understood as more important than others. The understanding may be influenced by the different interests groups and, therefore, based on intuition, subjective judgment and other non-objective ways of selecting a decision alternative. In order to contribute to make decision process as objective as possible, the use of decision support systems can significantly help in identifying the right solution to a given problem [2].

Because the decision making processes are applicable in different domains, the concept of decision support system is differently interpreted [7, 18, 9, 8]. For the purpose of this paper we define decision support system as a many types of information systems that support decision making [14].

Both fuzzy-logic and neuro-fuzzy modelling by their characteristics contribute to the improvement of decision processes in tobacco control. Fuzzy logic is a family of methodologies used in the analysis of incomplete, imprecise, or unreliable information. Tobacco control social regulation field is full of imprecise, incomplete and unreliable information that come from two different interests groups. One is health improvement oriented groups, while the others come from the tobacco, the hospitality and the entertainment industry [11]. Fuzzy logic enables approximate reasoning in which the rules of inference are approximate rather than exact [4]. Fuzzy (*if-then*) rules represent knowledge concerning the relationships between items. The accuracy of each rule is determined by membership functions [5].

The existing computational methods in tobacco control have been applied to investigate tobacco smoking policy regulations in Australia [5, 1, 12, 13]. The models comprising of two groups neuro-fuzzy systems and evolutionary algorithms were used to identify the factors influencing the effectiveness of measures to prevent tobacco smoking by people under 18 years.

The first group of methods, neuro-fuzzy systems comprises of both fuzzy logic and neural networks.

FUZZY CONTROL MODEL

The fuzzy control model implements "soft linguistic variables on a continuous range of truth values which allows intermediate values to be defined between conventional binary" [3], is extensively used in Artificial Intelligence programs [5].

The fuzzy control model has been applied in estimating the type of social regulation of tobacco control in Australia. The model comprises the following variables: compliance rate by retailers' obedience, maximum enforcement according to protocol, enforcement community education. Variables were presented in a membership form expressing explicit expert systems knowledge. *If… then* enforcement rules were introduced following the fuzzy control procedure. The accuracy of the model was tested with the data from local government areas in Melbourne, Australia. It indicated the influence of the different variables in different municipalities.

The model has limitations because it only covers the explicit knowledge based on social policies and procedures. It does not reflect tacit, indirect, knowledge of community based on local ethics and norms that can significantly reduce adolescent smoking rates. The model also does not provide government representatives with the answer to what extent to concentrate on available social regulation measures in anticipating enforcement efforts.

In spite of its drawbacks, the model demonstrates an estimate of the outcomes of social regulation given its formal provision of the social regulation regime [5]. As such, it represents a first attempt to support tobacco control decisions processes.

NEURAL NETWORKS MODELS

The neuro-fuzzy modelling is a type of Artificial Intelligence program based on neural networks and fuzzy models [12]. "A neural network is an information processing concept that is inspired by the way biological nervous systems process information. The key element of this concept is the novel structure of the information processing system composed of a large number of highly interconnected processing elements (neurones) working in unison to solve specific problems" [15]. Neural networks combine "simple processing elements, high degree of interconnection, simple scalar messages, and adaptive interaction between variables" [10]. Neuro-fuzzy modelling enables handling imprecision and uncertainty in data and refining them by a learning algorithm [3]. It creates fuzzy rules in easy-to-comprehend linguistic terms [13].

With the neuro-fuzzy modelling the derivation of *if-then* rules and corresponding membership functions depends heavily on the *a priori* knowledge about the system under consideration. The system can utilize human expertise by storing its essential components in rule base and database, and perform fuzzy reasoning to infer the overall output value. However, since there is no systematic way to transform experiences of knowledge of human experts to the knowledge base, the Adaptive Network Based Fuzzy Inference System (ANFIS) and Evolving Fuzzy Neural Network (EFuNN) models were introduced to apply the neuro-fuzzy support of knowledge management in social regulation [12]. Thus, the explicit knowledge was based on social policies and procedures to reduce smoking among youngsters, and the tacit knowledge was expressed through the applied membership functions. Empirical results showed the dependability of the proposed techniques.

Simulations were done with the data provided for the local government areas. Each data set was represented by three input variables and two output variables. The input variables considered were: compliance rate by retailers, enforcement according to protocol and community education. The corresponding output variables were compliance rate by retailers and compliance rate by retailers projected as estimated rate of smoking uptake by minors. ANFIS performed better than EFuNN in terms of performance error. EFuNN performed approximately 12 times faster that ANFIS. Depending on governmental requests it is possible to compromise between performance error and computational time.

Important disadvantages of ANFIS and EFuNN include the determination of the network parameters like number and type of membership functions for each input variable, membership functions for each output variable and the optimal learning parameters.

Both approaches ANFIS and EFuNN represent a systematic way to transform experiences of prior tobacco control regulations into a knowledge base. As such, in spite of the limitations, they can provide useful information for helping tobacco control decision makers to have sufficient information and minimise non-objective ways to selecting a decision alternative.

EVOLving POLicies

With modelling comprising both tacit and explicit knowledge a selection of optimal parameters may be formulated as an evolutionary search. This makes the neuro-fuzzy systems fully adaptable and optimal according to government representatives' requests by providing the answer to what extent to concentrate on available social regulation measures in anticipating smoking enforcement efforts.

Evolutionary algorithms transform a set of objects, each with an associate fitness value, into a new population using operations based on Darwinian principles of reproduction and survival of the fittest, and naturally occurring genetic operations. The evolutionary algorithms learning technique can optimize the human knowledge from the database [17]. In particular, the evolutionary algorithms technique may be helpful in the cases where expert knowledge is explained by a natural language or written words. Its usefulness is in encoding the fuzzy rules of the method of automatic database learning in the fuzzy control and neural networks learning models. It also minimizes the number of rules by including only the most significant ones [6]. The EvoPol (EVOlving POLicies), an evolutionary computation technique, was used to optimize the *if-then* rules to support governmental policy analysis in restricting recruitment of smokers. The proposed EvoPol technique is simple and efficient when compared to the neuro-fuzzy approach. It is useful in indicating to decision makers when to choose specific social regulation measures to control tobacco use. However, EvoPol attracts extra computational costs due to the population based hierarchical search process [1].

All created and tested models are related to adolescents. Although each one of them has potential to be further developed to include all tobacco users and, therefore have an implication to minimise negative effects of tobacco use, it seems that the knowledge based models provide more sufficient information to decision makers. Consequently, we propose a new learning technique; the fuzzy casual networks (FCNs).

THE NOVELTY OF THE PAPER

FCN is a dynamic networked system with feedback [19]. It evolved from a cognitive map and has been used as a qualitative tool fore representing casualty and dynamic information modelling. In any FCN there are three kinds of elements, namely the concepts, the casual relationships between concepts and the effects one concept influencing the other. By convention, we use vertex to represent the concept, directed arc to represent the causal relationship between two concepts, and numerical values in [-1, 1] associated with the directed arc to represent the effect of one concept on another. For each vertex, we assign a state value, which is quantified as a real number, to measure the degree of occurrence of a fuzzy event at a discrete time t. At any time, when a vertex receives a series of external stimuli, its state value is updated at the next time according to a state-transition function. Once constructed, the fuzzy casual network allows us to perform a qualitative simulation of the system and experiment with the model [20].

FCN is useful in tobacco control, since at the national/local government level within any country, all factors involved in tobacco control, such as smokers, non-smokers, researchers, doctors, advocates, tobacco industries and national/local economies, form a discrete dynamic system. Also, these factors interact each other and influence the effectiveness of tobacco control policies as a whole. So in nature the complex tobacco control system can be regarded as a dynamic networked system with feedback. In the application of FCN in tobacco control, the vertex represents a fuzzy event, such as smokers' behaviour and tobacco industry's response to tobacco control policies. According to scientific evidence, expert opinion and the nature of the tobacco market, we identify and choose some suitable vertex state values at a specific time as an initial condition. Also, we assign a state transition function for each vertex. After constructing a discrete dynamic system for the purpose of tobacco use control, we perform a qualitative simulation for this system. As a result, we can provide knowledge discovery and decision support to decision makers for tobacco control policy planning and development.

CONCLUSION

Changing tobacco control policies based on adequate information no doubt can contribute to minimising negative effects of tobacco use in any society. Therefore, attempts to use the decision support in the form of neuro-fuzzy models in tobacco control should be welcomed by each government. In this paper we have pointed out the theoretical contributions to this important field of social regulation, highlighting the advantages and disadvantages of each tobacco control method created and tested. We have also emphasized the use of Fuzzy Casual Networks to further help to improve the governmental decision making processes by including all factors involved in tobacco control.

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