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EVOPOL: A FRAMEWORK FOR OPTIMISING SOCIAL REGULATION POLICIES

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Abstract

The aim of the paper is to introduce EvoPol (EVOlving POLicies): an evolutionary computation (EC) technique to optimize the *if-then* rules to support governmental policy analysis in restricting recruitment of smokers. EC is a population based adaptive method, which may be used to solve optimization problems, based on the genetic processes of biological organisms. Parameters of the fuzzy inference system could be adapted using a neural network learning technique (neuro-fuzzy system) or by evolutionary computation. The fuzzy decision system (FDS) was developed based on three sub-systems: fuzzification, fuzzy knowledge base (*if-then* rules) and defuzzification. In this paper we propose the fine-tuning of fuzzy rule base and membership function parameters using an evolutionary algorithm. We compare the present work with our previous work using neuro-fuzzy techniques. Empirical results clearly show that evolutionary learning could perform better (improvement of decision score) than the neuro-fuzzy techniques at the expense of extra computation cost.

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DEPARTMENT OF MANAGEMENT

EVOPOL: A FRAMEWORK FOR OPTIMISING SOCIAL REGULATION POLICIES

INTRODUCTION

Tobacco smoking is associated with addiction to the nicotine content of cigarette smoke. Addiction to cigarettes commences as an uninformed and irrational action. Smoking by adolescents is related to emulating adult roles and is a symbol of belonging 0. Ill-health effects are too remote to be of concern 0. Recruitment of minors as smokers is different from the "rational addiction" of established adult smokers 0, and decisions by adults to continue or cease smoking. Early commencement of smoking is closely linked to both long-term smoking and heavy smoking 0. Access to cigarettes is a major factor in the high levels of smoking among minors0.

The effects of the extent of social regulation of the community has been studied in the particular instance of the regulation of access by minors to cigarettes in pursuit of the societal objective, expressed as public policy, of reduced incidence of smoking related ill-health and premature death. The public policy lends itself to study as there has been considerable attention to the issue for at least two decades in several jurisdictions, with a variety of specific policy measures and a range in the enforcement effort applied and compliance levels achieved. This has been extensively reported in the literature, including changes over time following the amendment of public policy and its enforcement 0.

Two types of models were applied to support knowledge management in social regulation 0 0. That is a fuzzy inference system with variables defined as membership functions expressing explicit expert systems knowledge in the form of fuzzy *If-then* rules with mechanism of reasoning in humanly understandable terms 0. Then, neuro-fuzzy models were based on tacit knowledge to point to what specific steps local government should undertake to reach the outcome with an increase in compliance. These models have disadvantages related to deciding the optimal quantity and shape of membership functions for both input and output variables and the parameters of the learning algorithms.

In this paper we propose an evolutionary algorithm to optimize the fuzzy *if-then* policies and the membership function parameters. In this respect the paper is divided as follows: Part 2 defines what has been done in terms of modeling in order to support governmental policy analysis in restricting recruitment of smokers. In Part 3 we summarize our previous work using neuro-fuzzy systems. Part 4 deals with the modeling of the problem using evolutionary algorithms followed by experimentation setup and results in Part 5. Some conclusions are also provided towards the end.

PROBLEM FORMULATION

In governmental knowledge management, as in any other knowledge management, a decision-making process is based on expertise knowledge to solve a problem. The expertise knowledge is usually stored in a system to be used to mimic the human way of reasoning and interpretation of a decision-making problem such as fuzzy logic, and neural networks learning methods.

Knowledge, described as natural language (spoken language) or using symbolic terms 0, relevant to governmental support in social regulation could be classified as national culture (how things work in the nation), social networks (who can do what) and models for solving problems. National culture is related to policies and procedures established through social regulation. But it is also related to ethics and core values of the society. Social networks and problem solving are associated with an individual or social groups.

Policies and procedures can be classified as an explicit knowledge or the knowledge that is codified and transferable in order to support decision-making. This knowledge relates to a community culture indicating how things work in the community based on social policies and procedures. On the other hand, tacit knowledge - which is personal knowledge, experience and judgement - is difficult to codify. But since it is expressed mainly through linguistic information it can be stored with a help of fuzzy inference system and could be further optimised using some learning methods.

WHAT IS KNOWN?

Fuzzy inference model

The fuzzy inference model was applied to estimate the type of social regulation among minors that can occur in many forms, including the informal social customs which govern interpersonal relationships, systems of belief and behavior mediated through religious and similar social institutions, constitutional arrangements and formal regulation established through legislative processes. The applied model considers of three variables: baseline condition (rate by retailers'), maximum enforcement according to protocol, and enforcement community education (no retailer education). Variables are defined as membership form expressing explicit expert systems knowledge. Then, *If…then* enforcement effort rules are introduced following the fuzzy control procedure. The applied fuzzy control model demonstrates an estimate of the outcomes of social regulation given its formal provision of the social regulation regime 0.

Although the model is based on expert systems, it has limitations. Firstly, it only covers explicit knowledge based on social policies and procedure. Secondly, it does not reflect tacit knowledge of community based on local ethics and norms that can significantly reduce adolescent smoking rates. Thirdly, the model does not provide government representatives with the answer to what extent to concentrate on available social regulation measures in anticipating smoking enforcement efforts.

Neuro-fuzzy models

Neuro-fuzzy systems make use of linguistic knowledge of fuzzy inference system and the learning capability of neural networks. Applied in social regulation they preciously model the uncertainty and imprecision within the data and incorporate the learning ability of neural networks. Neuro-fuzzy models implementing Tagaki-Sugeno Kang *if-then* rules and Mamdani type fuzzy inference systems are tested with tobacco smoking enforcement efforts 0. The Adaptive Network Based Inference System (ANFIS) based on Tagaki-Sugeno Kang *if-then* rules performed better than then Evolving Fuzzy Neural Network (EFuNN) based on Mamdani type fuzzy inference system in terms of performance error with a comprise on time. EFuNN performed approximately 12 times faster than ANFIS. A disadvantage of both ANFIS and EFuNN are the careful determination of the network parameters like number and type of membership functions for each input/output variable, optimal learning rates, an efficient algorithm to determine the rule, fuzzy operator parameters etc. Since the neural network-learning algorithm is based on gradient information of the error surface, there is no guarantee that the learning algorithm converges and the fine-tuning of the fuzzy system would be successful. In order to overcome some of the above difficulties, we propose EvoPol, an evolutionary algorithm based learning technique to optimize the fuzzy rule base and membership functions based on a hierarchical search process.

PROBLEM SOLUTION

Evolutionary algorithms (EA) are adaptive computational techniques that transform a set of objects, each with an associate fitness value, into a new population using operations based on Darwinian principle of reproduction and survival of the fittest, and naturally occurring genetic operations. The EA learning technique can optimize the human knowledge from the database 0. In particular, EA technique may be helpful in a case of social regulation of restricting recruitments of smokers where expert knowledge is explained by a natural language or written words.

The usefulness of EA technique is in encoding the fuzzy rules of the method of automatic database learning in the fuzzy control and neural networks learning models and minimizing the number of rules by including only the most significant ones [7]. In the following paragraphs we will explain how to model a Takagi-Sugeno fuzzy inference model using EA.

With the three fuzzy sets relevant for social regulation decisions support

A - base line condition (compliance rate by retailers' obedience)

B - maximum enforcement according to protocol
C - enforcement community education (no retailer education)

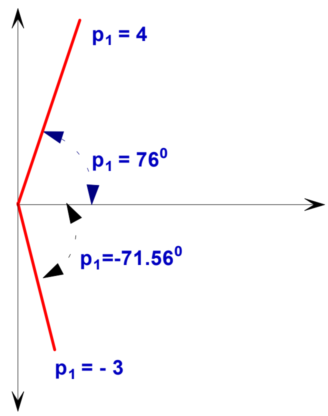
we used a grid partitioning algorithm to determine the initial rulebase. The optimal number of rules, representation of the antecedent and consequent parts is decided later. The number of rules grows rapidly with an increasing number of variables and fuzzy sets. The simplest way is that each gene represents one rule, and "1" stands for a selected and "0" for a non-selected rule. Figure 1 represents such a chromosome structure representation with m rules.

Figure 1. Chromosome representing the entire rule base consisting of *m* fuzzy rules

1	2	3		m-2	m-1	m
0	1	1	....	0	1	0

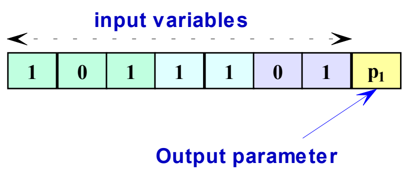
We used the angular coding method proposed by Cordon et al 0 for representing the rule consequent parameters of the Takagi Sugeno inference system. Rather than directly coding the consequent parameters, the "transformed" parameters represent the direction of the tangent α_i = *arctan* p_i. The range for the parameters α_i is the interval (-90, +90), such that the parameters p_i can assume any real value. A single input Takagi-Sugeno system $Y = p_1 X + p_0$ defines a straight line. The real value p_1 is simply the gradient between this line and the X-axis. Parameter p_0 determines the offset of the straight line (intercept) along the Y-axis. Angular coding is advantageous, since the value of p_0 varies between different rules and it is difficult to use some fixed interval to exploit the search space. The procedure is illustrated in Figure 2.

Figure 2: Angular coding technique of rule consequent parameters of Takagi-Sugeno inference system



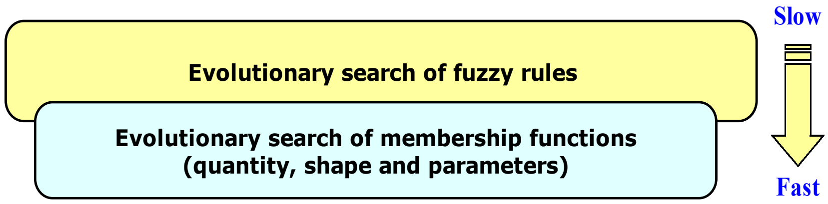
To represent a single rule a position dependent code with as many elements as the number of variables of the system is used. Each element will be a binary string with a bit per fuzzy set in the fuzzy partition of the variable, meaning the absence or presence of the corresponding linguistic label in the rule. For three inputs and one output variable, with fuzzy partitions composed of 3,2,2 fuzzy sets for input variables, the Takagi - Sugeno fuzzy rule (with a linear output parameter) will have a representation as shown in Figure 3.

Figure 3: Chromosome representation of a fuzzy rule



The rule base and the membership function parameters could be formulated as an evolutionary search wherein the knowledge base, membership functions (quantity and shape), parameters of MF etc. is evolved at different time scales as shown in Figure 4 0.

Figure 4: EvoPol framework for optimization of fuzzy inference system



Experimentation Set up and Test results

A two-year project was conducted in six local government areas (LGAs) of the western suburban region of Melbourne in the Australian State of Victoria. The relevant legislative provisions made it an offence for a person or their employee to sell tobacco to a person less than eighteen years of age. The initial intervention relied entirely on publicity and education of both suppliers and minors and others who were potential consumers of tobacco products. In two LGAs there were programs of education directed both at the community and at retailers specifically and enforcement through prosecution with supporting media reporting of successful prosecutions. In one, there were no educational programs but there was enforcement through prosecution with supporting media reporting of successful prosecution. In the three remaining areas – the control group - no change was made. However, the proximity of the six LGAs and the common exposure to metropolitan media reporting meant that the retailers and others in the control areas might have been exposed to news of the successful prosecutions. The project data were applied in the fuzzy decision system (FDS) based on three sub-systems: fuzzification, fuzzy knowledge base (*if-then* rules) and defuzzification.

The variables that influence the government social regulation of restricting smoking policy are presented in Table 1. For each LGA, 70% of the data were extracted randomly and used for training the EvoPol and building up the fuzzy inference system. Remaining 30% of the data was used for testing and validation purposes. The initial FDS was developed based on a grid-partitioning algorithm. The developed rules are initially encoded as shown in Figure 2 and further optimised by the evolutionary algorithm.

To limit the search space of the EA, we restricted to 2 Gaussian membership functions for each input variable as shown and the membership function parameters were encoded as shown in Figure 3. We used the direct encoding technique and the settings for the evolutionary algorithm is shown in Table 2. The parameter settings were finalized after a few trial and error approaches. Experiments were repeated 3 times and the average root means squared error (RMSE) values of the decision scores are reported.

Table 1: Variables that influence the Government smoking restriction policy

Baseline condition for miners	Maximum enforcement	Enforcement community education	Output
Occasional	Sufficient	Good	Do not change rules
Frequent smokers	Insufficient	Acceptable	Change some rules
Established smokers	-	Poor	Change all rules

Table 2: Parameter settings for EA

Population size	30
Maximum no of generations	50
Fuzzy inference system	Takagi Sugeno
Rule antecedent membership functions Rule consequent parameters	2 membership functions per input variable parameterized Gaussian angular coding
Ranked based selection	0.50
Elitism	5%
Starting mutation rate	0.40

Figure 5: EvoPol convergence after 30 generations

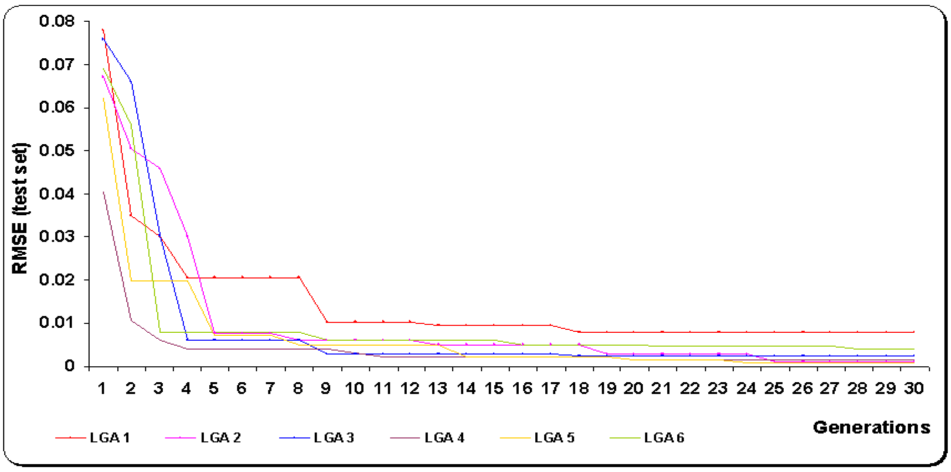


Figure 5 illustrates how EvoPol converged as the algorithm continued its global search for best solutions. Figure 6-11 illustrates the fine-tuning of membership functions for the 3 different inputs for LGA1. Figure 12 depicts the developed Takagi-Sugeno fuzzy inference system after 30 generations of EvoPol learning. We were not able to reduce the number of rules (8 rules). Due to space restrictions, the graphical results of other 5 LGA's are not depicted in this paper. The empirical results for all the 6 LGA's are depicted in Table 3. The efficiency mentioned in Table 3 is calculated as follows:

$$Efficiency = \frac{RMSE_{Test\ set}(NF) - RMSE_{Test\ set}(EvoPol)}{RMSE_{Test\ set}(NF)}$$

Figure 6: LGA1, input 1: MFs before EvoPol learning

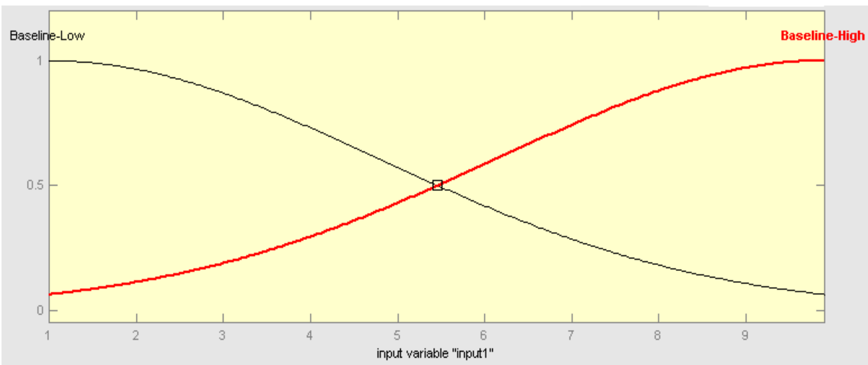


Figure 7: LGA1, input 1:MFs after EvoPol learning

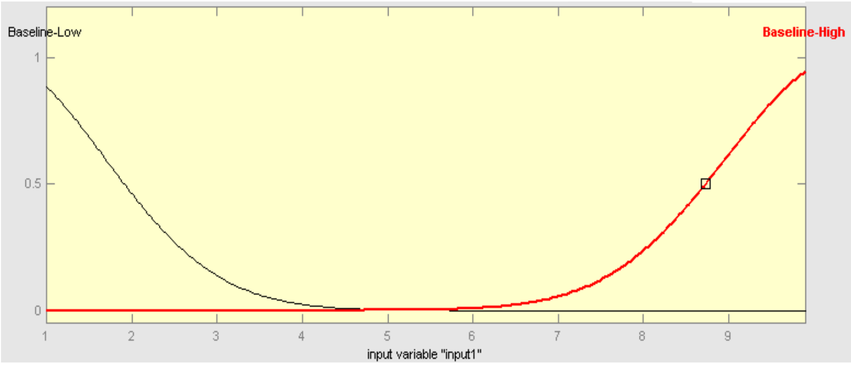


Figure 8: LGA1, input 2: MFs before EvoPol learning

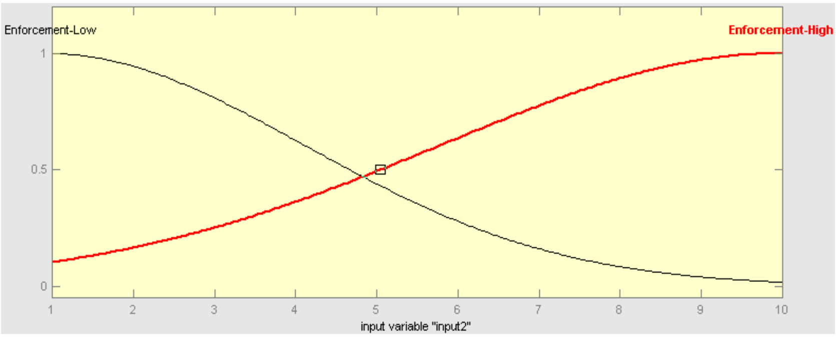


Figure 9: LGA1, input 2: MFs after EvoPol learning

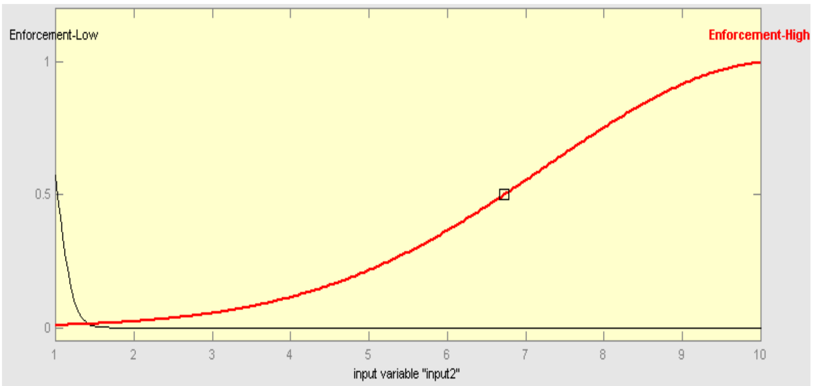


Figure 10: LGA1, input 3: MFs before EvoPol learning

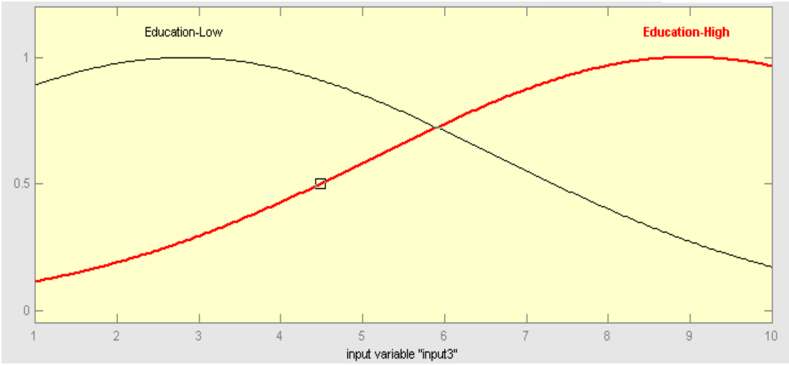


Figure 11: LGA1, input 3: MFs after EvoPol learning

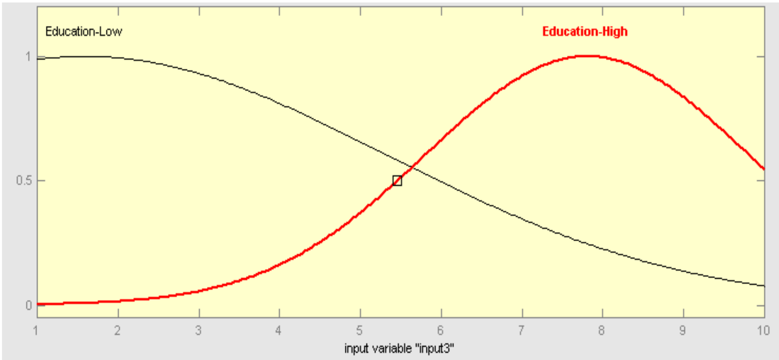


Figure 12: Developed Takagi-Sugeno FIS using EvoPol

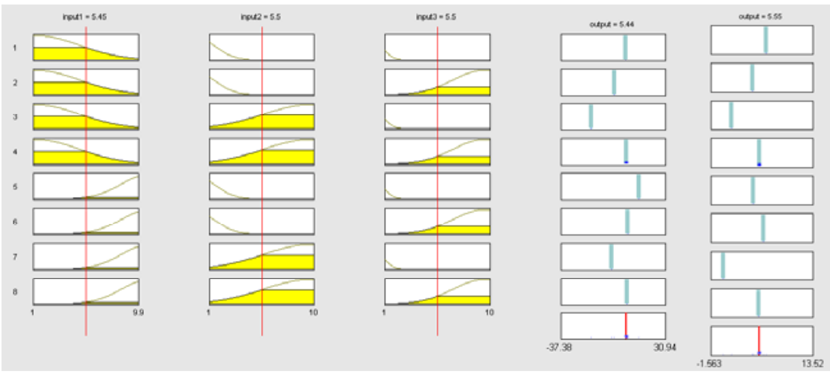


Table 3. Comparison of EvoPol and ANFIS

LGA	EvoPol		ANFIS (NF)		Efficiency %
	RMSE				
	Train	Test	Train	Test	
1	6 E-5	0.009	8 E-5	0.0171	47
2	6 E-4	0.011	6 E-4	0.0450	76
3	6 E-4	0.011	6 E-4	0.0450	76
4	2 E-4	0.009	2 E-4	0.0375	76
5	2 E-4	0.006	2 E-4	0.0185	68
6	3 E-3	0.008	3 E-3	0.0200	60

CONCLUSION

The proposed EvoPol technique is simple and efficient when compared to the neuro-fuzzy approach. However, EvoPol attracts extra computational cost due to the population based hierarchical search process. When compared to neuro-fuzzy model (ANFIS) the RMSE values on the test sets have improved considerably. Hence when policy makers require more accuracy EvoPol seems to be a good solution.

It is interesting to note that we were not able to reduce the number of fuzzy rules (8 nos) for each LGA. Perhaps this is because of the minimal number of MF's per input variable. For complicated problems involving more input variables, EvoPol would be an excellent candidate for framing *if-then* rules. Even though evolutionary algorithms are good global search algorithms, very often they miss the good local solutions. In our future work we would like to explore meta-learning techniques 0 combining EA and neural network learning algorithms to examine whether we could further improve the decision scores to help government representatives by providing the more accurate answer as to what extent to concentrate on available social regulation measures in restricting the recruitment of smokers.

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